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Data Driven Insights in Perioperative Workflows

An exploratory study using data to evaluate workflow disruptions and their implications in healthcare

Master's thesis in Biomedical Engineering

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CHALMERS UNIVERSITY OF TECHNOLOGY
Gothenburg, Sweden 2026
www.chalmers.se

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Cover: An image depicting a storage unit at a Swedish hospital, storing Mölnlycke products. Taken with signed permission from said hospital.

Typeset in LaTeX
Printed by Chalmers Reproservice
Gothenburg, Sweden 2026

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Abstract

Operating room (OR) workflows are characterized by complex material flows, strict time constraints, and high coordination demands. Disruptions in perioperative material preparation, particularly during the picking phase performed by OR nurses, represent an important but underexplored source of inefficiency.

This thesis investigated how material-related OR workflow data can be used to analyze workflow behavior, identify disruptions and inefficiencies, and generate insights relevant for decision support. The study was exploratory and based on shadowing data from a Swedish hospital, complemented by semi-structured interviews and, where necessary, synthetic data. The work was conducted in collaboration with Mölnlycke Health Care.

The findings suggest that disruptions in the picking process are closely connected to information fragmentation, unclear material availability, reliance on tacit knowledge, and changes in the surgical schedule. The quantitative analysis illustrated how variables such as picking duration, interruptions, waiting time, information search, perceived complexity, and staff experience could describe workflow variation. However, due to the small sample size and data limitations, the results should be interpreted as exploratory and indicative, rather than statistically generalizable.

Process mapping, visualization, and process mining demonstrated how material-centric workflows can be made more visible and interpretable for different stakeholders. The thesis contributes a framework for understanding perioperative material workflows and highlights the need for high-quality structured data to support future workflow analysis, stakeholder-adapted visualization, and clinically meaningful decision support.

Keywords: perioperative workflow, OR workflow, material picking, workflow disruptions, process mining, data-driven decision support, stakeholder-adapted visualization, healthcare digitalization.

Acknowledgements

We would like to express our greatest thanks to everyone providing support during this thesis. Especially to our supervisor, Maria Sjödin, for believing in this project and allowing us to perform it together with Mölnlycke Health Care. And a big thanks to our examiner, Xuezhi Zeng, for your valuable feedback and support throughout the process.

Karl Ahlgren & Love Stoopendahl, Gothenburg, June 2026

List of Acronyms

Below is the list of acronyms that have been used throughout this thesis listed in alphabetical order:

AI	Artificial Intelligence
GC	Green Cross
IT	Information Technology
KPI	Key Performance Indicator
MDR	Medical Device Regulation
OR	Operating Room
VIF	Variance Inflation Factor

Contents

List of Figures

List of Tables

1 Introduction

Operating rooms (ORs) constitute one of the most resource-intensive and time-critical environments within modern healthcare systems [1]. Despite ongoing digitalization efforts, many hospitals continue to rely on analogue practices, such as handwritten checklists and manual communication, for surgical preparation and intra-operative coordination [2]. These practices introduce several challenges related to documentation accuracy, information accessibility, and workflow predictability, which in turn can contribute to delays, interruptions, and increased cognitive load among clinical staff [3]. One of the persistent issues affecting OR efficiency is the frequent rescheduling of planned surgeries. These changes often propagate through the daily schedule, affecting resource availability and increasing the burden on healthcare personnel.

In response to these challenges, Mölnlycke Health Care has initiated efforts to explore how digital tools can support more structured and reliable OR workflows [4]. As part of this work, the company has developed a software concept intended to integrate with existing surgical routines and provide healthcare personnel with a digital interface for managing tasks, tracking material usage, and maintaining situational awareness throughout the surgical process.

A digital system of this nature extends beyond operational support; it also enables systematic data collection across the full perioperative trajectory. By capturing information from the early planning stages through the completion of surgery, hospitals gain access to datasets that reflect material consumption, temporal patterns, and workflow variations. Such datasets can provide a foundation for quantitative analysis aimed at identifying bottlenecks, inefficiencies, and recurring sources of disruption within OR operations [5].

1.1 Background

To understand the operational challenges addressed in this thesis, it is necessary to first examine the context in which surgical workflows take place. ORs represent highly coordinated environments where multiple professional roles, technological systems, and logistical processes must function together under strict time and safety constraints [6]. The activities surrounding surgical procedures extend beyond the surgery itself and involve a sequence of interconnected stages that collectively form the perioperative process. Understanding this broader workflow is essential for identifying where inefficiencies, disruptions, and material-related challenges may arise, and how data-driven approaches could contribute to improving coordination and operational efficiency.

1.1.1 The Perioperative Surgical Environment

Surgical procedures are performed within what is commonly referred to as the perioperative workflow. This workflow involve all the activities preoperative, intraoperative, and postoperative phases of surgical care. This includes preoperative planning, picking and preparation of surgical materials and the OR, the surgery itself, and postoperative cleaning and recovery.

To ensure that these activities operate seamlessly together between the different roles, departments, and patients, operational efficiency is key. As OR time is both costly and limited, hospitals place strong emphasis on maximizing the operational efficiency while simultaneously not letting it affect patient care and safety. Even the smallest inefficiencies in preparation activities or misses in coordination between staff members could lead to the start of a domino effect, increasing delays, workload, and reducing the capacity and utilization of the OR [1].

Within the perioperative environment, many tasks must be completed within strict time constraints and according to well defined safety protocols [7]. These include verification of patient information, preparation of sterile instruments, confirmation of surgical materials, and coordination between the surgical team and supporting units such as schedulers and sterile processing departments, and at the same time cohere to safety standards to upheld patient safety and care. The complexity of these activities means that surgical workflows often rely heavily on both formal procedures and implied knowledge developed through years of clinical experience.

1.1.2 Problems in Surgical Environment

Within surgical preparation, a critical component is the management of sterile instruments and consumable materials required for each procedure. Surgical interventions typically require a large number of items, from instrument trays to drapes, sutures, and implants [8].

The process of collecting, verifying, and preparing all the necessary materials is often a typical bottleneck process, where logistical challenges are frequent [4]. Missing or misplaced items, incomplete picking lists, or uncertainties regarding location of materials results in interruptions during the preoperative phase. This causes more cognitive load on the clinical staff, leading to more delays and inefficiencies in the later stages of the surgical workflow.

In addition, unexpected events such as surgery cancellations or rescheduling can further complicate the surgical workflow. Frequent rescheduling of planned surgeries is one of the most persistent issues affecting the surgical workflow [9]. Changes in the surgical schedule may require rapid adjustments in material preparation and resource allocation, increasing the risk of errors, delays, and inefficient utilization of OR resources.

In modern healthcare systems, these challenges are today often addressed through verbal communication, supplemented by informal tools such as handwritten notes and telephone communication between different departments [4]. However, this approach limits the accessibility and consistency of critical information among clinical staff. As a result, relevant workflow information may be fragmented across multiple sources, making it difficult to obtain a comprehensive overview of operational activities [10].

1.1.3 Industrial Context: Mölnlycke Health Care

Mölnlycke Health Care is an international medical solutions company specializing in products and services used in surgical procedures and wound care [8]. The company collaborates with healthcare providers worldwide to develop solutions aimed at improving clinical outcomes, operational efficiency, and patient safety within healthcare environments. Within the context of surgical workflows, Mölnlycke works closely with hospitals to understand operational challenges related to material handling, sterile supply management, and the preparation of surgical procedures.

Mölnlycke's initiated efforts are aimed at digitalizing the picking process and integrating relevant surgical information from multiple systems. The objective for the concept is to improve information accessibility and reduce unnecessary interruptions in the workflow.

In the current predominantly analog hospital environment, access to information can be limited, particularly for less experienced staff. For example, locating specific items may require interrupting the picking process to consult colleagues, potentially disrupting ongoing tasks and reducing overall efficiency.

The proposed solution from Mölnlycke addresses three phases corresponding to the perioperative workflow: picking, preparation, and surgery. The solution does not interact with patients or handle sensitive patient data, and therefore does not meet the criteria of a medical device as defined in Article 2 of the Medical Device Regulation (MDR) [11]. By introducing the digital solution in the surgical workflow, certain data points can be monitored that has not yet been recorded in a structured, systematic, and reliable way.

The study aims to contribute to a better understanding of how data generated within surgical environments can be structured, analyzed, and presented in ways that support data-driven decision-making and workflow improvements in healthcare organizations.

1.2 State of the Art

Previous research on OR workflows has primarily focused on surgical scheduling, resource utilization, and overall procedure durations. Data-driven approaches, including process mining and machine learning, have been widely applied to identify bottlenecks and improve efficiency in perioperative processes [12]. These studies typically rely on structured event data extracted from hospital information systems, enabling the analysis of workflow patterns and deviations.

A structured literature search in PubMed indicates a substantial body of recent research on OR workflows, with several hundred publications in the past five years. However, when narrowing the search to include terms related to material picking or instrument preparation, a very limited amount of studies were identified that explicitly address this aspect of the workflow. This suggests that, while OR efficiency has been extensively studied, the material preparation phase, particularly the picking process performed by OR nurses, remains very underexplored.

Similarly, searches related to preoperative workflows yield a large number of publications, often focusing on patient-related factors, surgical techniques, or imaging methods used to support surgical planning. A review of a subset of these studies did not reveal any explicit focus on the picking process or material handling activities carried out by clinical staff. This indicates a research gap in understanding the operational and cognitive aspects of material preparation within the perioperative workflow.

Taken together, the literature suggests that OR workflows and efficiency have been extensively studied, particularly in relation to scheduling, resource utilization, patient flow, and overall procedure duration. However, the material picking process remains underexplored, despite its relevance for workflow efficiency, information access, and staff workload. By focusing on the picking process from the perspective of OR nurses, and exploring how workflow data can be presented to support decision-making for different stakeholders, this thesis contributes to a much less examined area of perioperative workflow research.

1.3 Purpose

The purpose of this thesis is to contribute to a better understanding of how operational data from perioperative material related workflows can be used to support analysis, interpretation, and decision-making in surgical environments.

Furthermore, the thesis addresses the need for approaches that can make partial and context-dependent workflow data more useful for analytical purposes. The study seeks to explore how structured analysis of material-related OR data based on qualitative contextual input, can support a more informed understanding of workflow behavior and its operational implications.

The thesis is further motivated by the need to communicate analytical findings in ways that are accessible and relevant to different stakeholder groups in healthcare organizations. By examining both the analytical use of workflow data and the presentation of derived insights, the study aims to contribute knowledge that may support future data-driven improvements in perioperative planning, coordination, and resource management.

1.4 Aim

The aim of this thesis is to investigate how material-related OR workflow data can be used to analyze workflow behavior, identify inefficiencies and disruptions, and generate insights that are relevant for decision support in a surgical context.

The study is grounded in empirical workflow data, which forms the basis for exploratory analyzes. Due to the limited and partially incomplete nature of the data, qualitative input is used to support interpretation and contextualize the observed workflow patterns.

In addition, the thesis aims to explore how the results of such analyzes can be structured, communicated, and presented in a stakeholder-adapted manner. This includes examining how analytical insights may be translated into decision support that are interpretable and practically relevant for different users within the surgical environment.

The work is exploratory in its nature and does not seek to produce statistically generalizable conclusions. Instead, it aims to examine how data, when contextualized appropriately, can serve as a foundation for structured analyzes and future decision-support development.

1.5 Delimitations

In this thesis, the OR workflow serves as the structural backbone for data modeling, data collecting, and subsequent analysis. The specific data collected, is organized according to a simplified representation of the OR process, capturing the temporal order of events and material-related activities. This abstraction allows workflow behavior to be analyzed without reliance on full clinical system integration, or patient-specific data.

The study is delimited to material-related and personnel-related aspects of the perioperative workflow. The focus is placed on activities connected to surgical material handling, picking, preparation, information access, interruptions, and coordination between healthcare personnel. Patient flow, clinical outcomes, surgical techniques, and postoperative recovery are therefore outside the scope of the analysis.

The thesis is further situated within a Swedish healthcare context, with particular relevance to hospital environments connected to Mölnlycke's customer setting. Organizational routines, roles, terminology, and material handling practices may differ between countries, regions, and hospitals. Consequently, the findings should be interpreted in relation to a hospital in the Swedish perioperative context, in which the empirical data and contextual insights were obtained.

It is important to note that trauma cases and elective cases can differ significantly in their preparation requirements, particularly in hospitals that operate trauma units. For the purpose of this thesis, the focus is placed on elective cases, as these procedures are planned and scheduled in advance. Trauma cases are inherently unpredictable and therefore cannot be used to prepare for and analyze within a structured workflow model, therefore falling outside the scope of this study.

The work does not aim to deliver a production-ready system or a certified medical solution. Instead, it is intended to produce transferable knowledge and architectural insights that can inform future development.

The analysis in this thesis is constrained by the availability of empirically collected data, which is partially incomplete. These gaps were addressed through complementary qualitative data, which was acquired through expert interviews and contextual analysis, as well as imputed data points, rather than through large-scale quantitative data collection.

As a result, the findings are not intended to be statistically generalizable beyond the observed hospital context. Instead, the thesis focuses on demonstrating how meaningful analyzes and presentation of insights can be achieved using partially complete empirical data, with complementary qualitative information used to contextualize identified gaps.

2

Theoretical Framework

The following chapter presents the theoretical framework that motivates the modeling of operating room workflows, the application of interpretable analytical methods, and the importance of presenting data correctly. It also presents the state of the art in the current landscape.

2.1 Operating Room Workflow

OR workflows consist of a sequence of tightly coupled activities involving personnel, materials, and time-critical coordination [6]. Disruptions in these workflows, particularly those related to material availability and preparation, are a well documented source of inefficiency in hospital operations [4]. To enable a data-driven analysis of such disruptions, a clear conceptual model of the OR workflow is required.

An OR workflow can be understood as the interaction of multiple interdependent flows, most notably patient flow, surgical flow, and sterile supply flow [6]. From patient admission to discharge, these flows operate in symbiosis to ensure a streamlined and optimized workflow across the sterile supply chain, the OR, and the broader perioperative pathway. This thesis addresses the surgical and sterile supply flow, as it aims to elaborate, explore, and understand the healthcare personnel's role in the clinical setting. As the operating suite represents one of the most resource-intensive areas of the hospital, effective workflow support is a key determinant of patient safety, cost efficiency, and the working environment of healthcare professionals [1]. Well designed workflows enable clinical staff to focus on their primary objective: delivering safe, and high-quality care.

Empirical studies in Swedish hospitals have demonstrated that workflow inefficiencies in the operating suite can often be traced to preparation and material handling practices. In one such example, the introduction of dedicated preparation rooms for sterile equipment, shifting preparation activities away from the OR, led to reduced staff stress and an increased number of surgical procedures performed annually [13]. Previously, preparation had been conducted inside the OR, contributing to interruptions and inefficient use of OR time. This is just one of many different ways in which targeted changes to workflow design and task allocation can mitigate operational bottlenecks and improve overall OR efficiency.

By modeling the OR workflow as a sequence of distinct phases, it enables identification of material-related events and when they occur, relevant data points for analysis, and which inefficiencies propagate across the workflow.

For the purpose of this thesis, the OR workflow is divided into four main phases: picking materials for surgery, preparation, intraoperative activities, and postoperative activities. This phased abstraction does not aim to represent a complete surgical process model. As discussed in Section 1.5, it allows key workflow behaviors to be analyzed without reliance on full clinical system integration, while providing the theoretical foundation necessary to understand existing gaps and improvement opportunities.

Information from *Mölnlycke*, about OR workflows and their digital solution, is obtained through confidential company documentation, under a non-disclosure agreement.

2.2 Process Model of the OR Workflow

To support the reader's understanding of the OR workflow, this thesis introduces a process map, Figure 2.1, describing the main phases and activities involved in the surgical workflow. Presenting the workflow as a process map provides an overview of these interactions, and clarifies how different activities intervenes and relate to each other. This overview also serves as a theoretical foundation for the subsequent analysis of workflow events and operational disruptions.

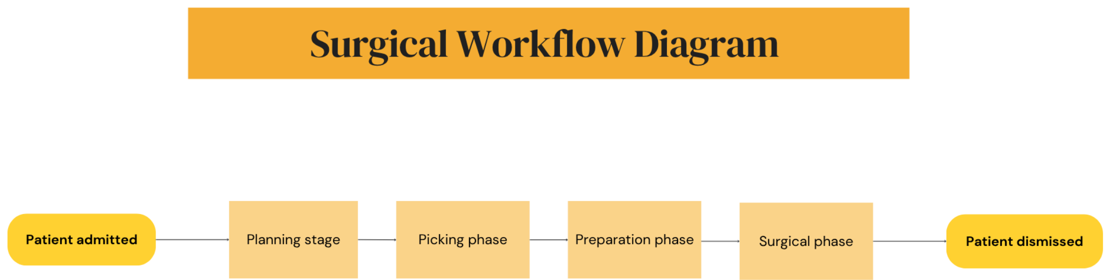

Figure 2.1: A process map of the surgical workflow

2.2.1 Picking

The OR workflow begins with the picking of materials required for the surgery. This task is generally performed by the OR nurse stationed in the corridor, whose responsibility is to first collect information about the scheduled procedure [4]. This information typically includes the Surgery ID, surgeon preferences, and relevant patient information. Each type of surgery is associated with a specific identifier. Surgeon preferences may include requirements such as left-handed instruments, surgical intervention preference, specific glove sizes, or a preference for particular types of sutures [14].

The next step for the OR nurse is to collect the necessary equipment for the surgery based on the procedure card [4], [14]. After verifying that the information on the procedure card is correct, sterile items are collected. This typically involves locating the appropriate trolley containing sterile equipment and matching the Surgery ID on the pick list [4]. Additional items may need to be collected from storage areas outside the preparation or OR. Once all required materials have been gathered, they are transported to the target location.

If additional information is required during the picking process, the OR nurse may consult the surgeon, review procedure cards, or seek clarification from colleagues. The nurse may also refer to physical documentation, such as inventory binders, before retrieving the required items. When item locations are unclear, other departments may need to be contacted; if the item cannot be located internally, external hospitals may be consulted.

The picking process has been identified as the component of the OR workflow most frequently associated with operational challenges, including interruptions, waiting times, delays, and time spent searching for information. These factors contribute to increased cognitive load for clinical staff and make the picking process a significant source of workflow unpredictability.

The duration of the picking process may vary depending on several factors, including the complexity of the surgery, the number of required instruments, the experience of the nurse performing the picking, and the availability and location of the required materials. Interruptions, missing items, or the need to search for additional information may further increase the time required to complete the process. As a result, the picking phase represents a critical point in the OR workflow where inefficiencies and delays can propagate to subsequent stages of the surgical preparation process.

To provide a structured overview of the picking process, a simplified process map of the picking workflow is presented in Figure 2.2. The process map illustrates the main activities and their sequential relationships as they are conceptually described in the workflow. Figure 2.2 could also be found as an enlarged version in Appendix B, as Figure B.1.

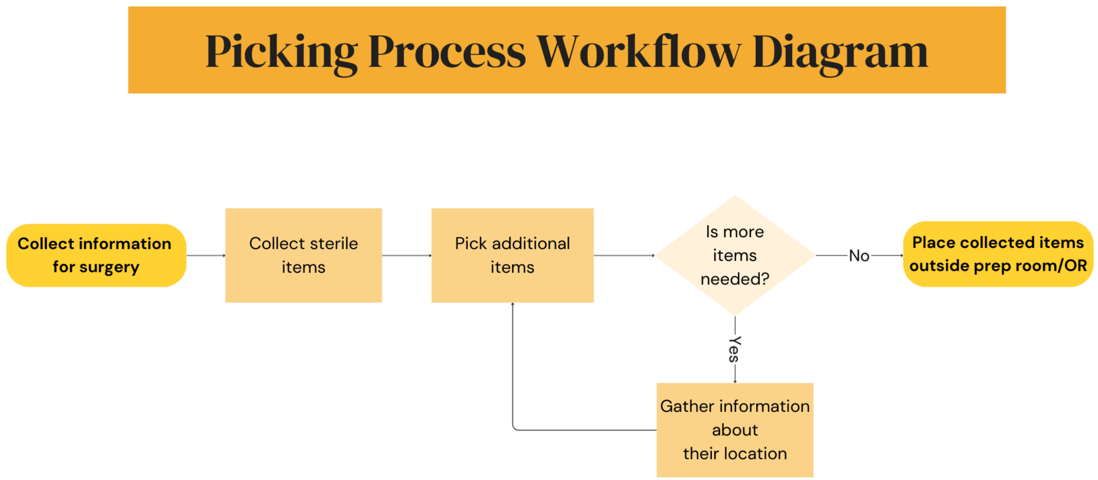

Figure 2.2: A process map of the picking process workflow

However, real-world workflows rarely follow such a strictly sequential structure. In practice, the picking process often contains deviations such as interruptions, repeated activities, waiting periods, transportation time, and information searches. A more realistic representation of how the workflow may appear in practice is illustrated in Figure 2.3. This process map is enlarged in Appendix B, as Figure B.2.

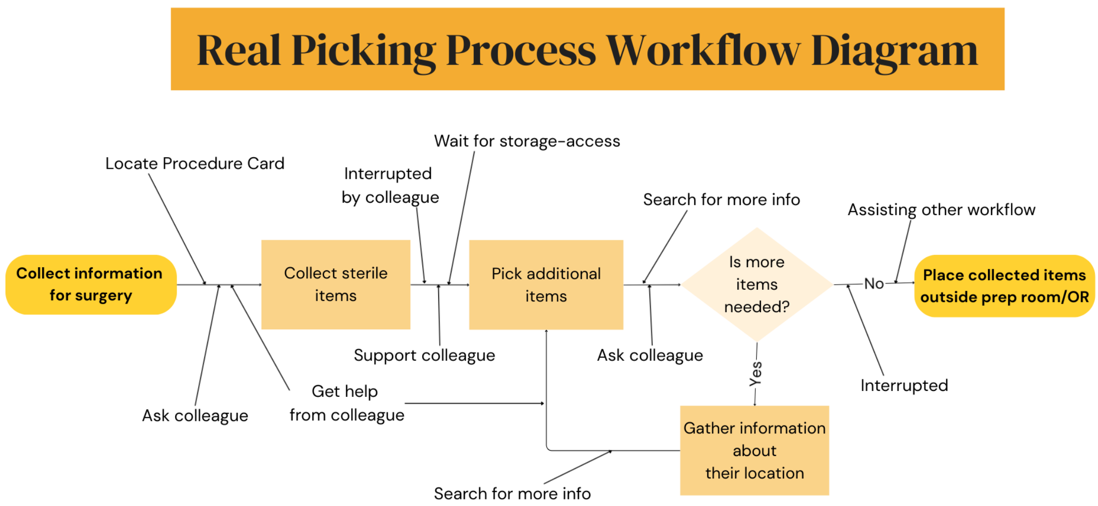

Figure 2.3: A process map depicting the reality of the picking process workflow

2.2.2 Preparation

After the picking process is concluded, the preparation phase begins [4]. In parallel with the patient's preparation for surgery, an OR nurse and an assistant nurse begins with the preparation of the surgical materials.

While the assistant nurse verifies the initial information, such as confirming the contents of the material cart and the patient ID, the OR nurse scrubs in to assume the role of the sterile nurse. The assistant nurse opens the sterile packages, while the sterile nurse removes the items and places them in the sterile field [6]. The sterile nurse then counts the items, checks their sterility, and arranges them according to the surgeon's preferences [4].

This process is repeated for all items required for the procedure, after which the preparation table is draped accordingly. Once all materials have been prepared, the OR nurse confirms the final count of instruments and materials. If the preparation is performed outside the OR, the prepared materials are subsequently transported into the OR, where the material workflow intersects with the patient workflow.

The duration of the preparation phase varies depending on factors such as the number of instruments required, the complexity of the procedure, and the occurrence of interruptions. Although interruptions are generally kept to a minimum in order to preserve the sterile field, they may still occur when the sterile nurse or other colleagues need to consult one another. Given the high stress environment, a trade-off could arise between minimizing preparation time and adhering to all the standards for counting sterile items. Delays in preparation may directly impact the scheduled start time of the surgical procedure.

2.2.3 Intra- and Postoperative Activities

In the context of this thesis, intra- and postoperative activities are described briefly, only to provide a complete overview of the OR workflow.

Once the patient and prepared surgical materials have been transferred into the OR, the intraoperative phase begins [6]. During this stage, the surgical team performs the procedure while the sterile nurse assists the surgeon by providing the required instruments and maintaining the sterile field. The circulating nurse supports the procedure by retrieving additional materials if required. The sterile nurse continuously counts the items used during the procedure.

Following completion of the surgery, the postoperative phase begins. The patient is transferred to a recovery unit, while used instruments and materials are removed from the sterile field and transported for cleaning, disinfection, and sterilization. Single-use items are deemed consumed, implying that they are either used or thrown away, as they cannot be reused. The OR is subsequently cleaned and prepared for the next procedure. The OR nurse document count for the items used, instrument trays, gauzes, and sutures.

After the surgery, materials that have been picked and prepared for the surgery end up either consumed or contaminated. The material workflow is visualized in a simplified process map to create a better understanding for the reader. The process map is found in Figure 2.4.

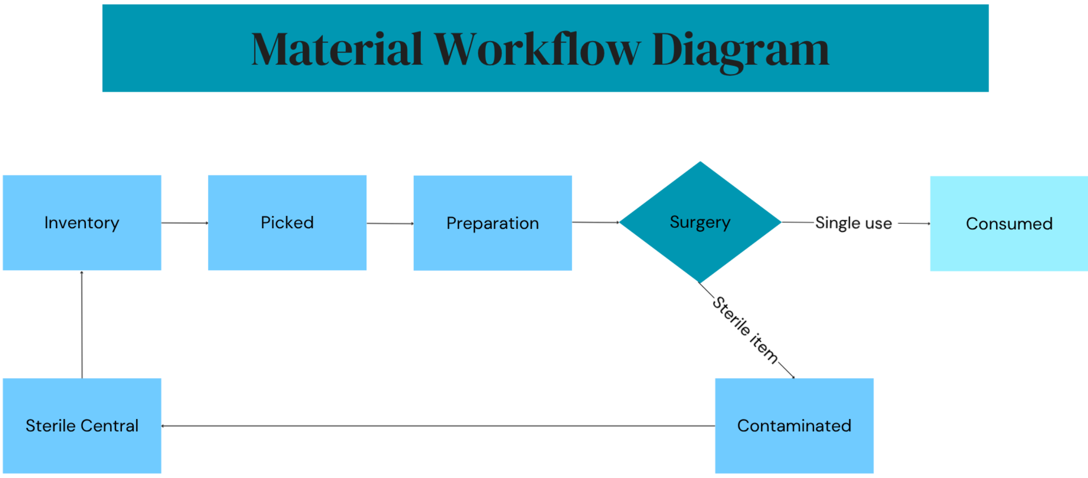

Figure 2.4: A process map of the material workflow

2.2.4 Rescheduling of Surgeries

All scheduled surgeries carry an inherent risk of cancellation or rescheduling due to a range of factors [15]. These may include patient-related issues, such as non-compliance with preoperative instructions or a decline in the patient's condition. Reschedules could also happen due to organizational constraints, including limited staff availability, missing or unprepared materials, or insufficient OR capacity. In addition, emergency cases may take priority, requiring immediate reallocation of resources [4].

Compared to routine interruptions, rescheduling events introduce more significant disruptions, as they can occur at any phase of the workflow [15]. This means that after a picking phase has been finalized, or even after the preparation is completed, the surgery can be canceled. The consequences are an increasing risk that already prepared sterile materials becomes contaminated or unusable, leading to unnecessary time loss, resource waste, and increased operational costs.

The responsibility to communicate information about rescheduled or canceled surgeries falls on a designated person within the department [15]. This person is often under high workload and time pressure, causing the information to sometimes not reach its receptors in adequate time. This highlights the need for a more streamlined information flow to prevent unnecessary work, such as preparing for surgeries that are ultimately not performed.

2.3 Digitalization in Healthcare

Digitalization in healthcare refers to the integration of digital technologies and information systems. Digital transformation is an ongoing process that can create opportunities in the health sector, provided that the necessary infrastructure and training are available [16]. Digital health technologies also refers to the communication and administrative technologies, including electronic health records, mobile health applications, telemedicine systems, scheduling systems, and analytical tools that support collection and subsequent analysis of healthcare flows and data.

The adoption of digital technologies has increased rapidly in recent years as healthcare systems seek to address growing demands, resource constraints, and increasing process complexity [16]. Digital transformation has been shown to improve healthcare service delivery by enabling more efficient communication, reducing administrative workload, scheduling appointments, providing medical information, and facilitating data-driven decision making [17].

The availability of structured digital data also enables the application of data-driven analytical methods, including machine learning and AI [18]. These approaches rely on event data generated by information systems to model real-world processes and identify deviations, bottlenecks, and opportunities for improvement.

In the context of OR workflows, digitalization can support more efficient coordination of clinical activities, reducing administrative and scheduling bottlenecks, and establishing powerful communication among healthcare professionals [15]. By improving access to reliable information, digitalization may contribute to more streamlined perioperative workflows.

2.4 Data in the Surgical Workflow

Data in surgical workflows can be of different types, such as time-event and metadata [19]. These data can be further classified as either real-world or synthetic, depending on their origin.

Time-event data capture when specific activities occur within the workflow [19], enabling the reconstruction of temporal sequences and identification of delays or inefficiencies. In contrast, metadata provide contextual information that describes the conditions, actors, and circumstances surrounding these events, supporting a more comprehensive understanding of the workflow [20], [21].

Together, these data types enable the analysis of when, how, why, and how often events occur within surgical workflows. This facilitates the identification of patterns, disruptions, and potential areas for optimization, ultimately contributing to improved efficiency and clarity in decision-making in the OR environment. As such, they function as analytical enablers by providing context, provenance, and interpretability to quantitative data.

A structured table is shown in Table 2.1 to give an overview of the different data types in the surgical context.

Table 2.1: Overview of data types in surgical workflow

Data Type	**Description**	**Example**
Time-Event Data	Captures when events occur	Timestamp of incision start
Metadata	Provides contextual information	Surgeon, cause of delay

2.4.1 Synthetic Data

Synthetic data refers to data generated outside traditional data collection processes, such as studies or surveys, and can complement real-world data by increasing volume, enabling faster development, and supporting anonymization [22]. It is widely used in applications such as machine learning, where deep learning methods have shown strong performance in generating realistic data [23]. According to Gartner, synthetic data is expected to surpass real-world data in machine learning applications by 2030 [24]. Its main advantages include cost-effectiveness, privacy, and accessibility, particularly in healthcare, where real-world data is often restricted due to legal and ethical constraints.

In cases where real-world data is unavailable, simulation-based approaches can be used to create synthetic data. These rely on domain knowledge and system modeling to generate representative data, supporting anonymization and reducing the risk of re-identification [25]. However, such data is dependent on assumptions and may not fully reflect real-world conditions, meaning results based on synthetic data should be interpreted with caution. In the context of this thesis, synthetic data is used as minimally possible, based on the stated concerns.

2.5 Relevant Stakeholders

By implementing Mölnlycke's digital solution in the perioperative workflow, multiple stakeholders can get valuable insights. These insight carry different weight depending on the stakeholders relation to the hospital operation. In this thesis, stakeholders refer to the following actors from both surgical and administrative settings:

- **OR Personnel:** The healthcare personnel working in and around the ORs.
- **Surgeons:** Personnel with procedure-specific requirements and preferences that influence preoperative planning, determining which materials are required for surgery.

- **Administrative personnel:** Staff responsible for scheduling surgeries, coordinating personnel, and managing information related to planned procedures and workflow changes.
- **Inventory and Sterilization personnel:** Staff responsible for material availability, inventory management, sterile supply handling, and reprocessing of surgical instruments.
- **Hospital Management:** Decision-makers responsible for operational performance, resource allocation, workflow improvement, and long-term strategic planning within the hospital.
- **Mölnlycke Health Care:** The industrial stakeholder behind the digital solution, with an interest in understanding clinical workflow needs and developing digital tools to support that workflow.

2.6 Presentation of Data

An identified limitation in current practice concerns the presentation of analytical results. Healthcare researchers struggle to take advantage of the potential to effectively communicate meaning in their data [26]. Although many systems generate large volumes of operational data, insights are often communicated through fragmented reports, or dashboards that are poorly adapted to the needs of different stakeholder groups [27]. Dashboards (containing for example Key Performance Indicators (KPIs)) often assume certain level of numeracy and graph literacy of their consumers to be effective. This reduces the practical impact of analytical findings and hinder their translation into actionable decisions at strategic, tactical, and operational levels.

2.6.1 Data Storytelling

Data storytelling refers to the practice of weaving data into a coherent narrative in order to enhance comprehension, engagement, and the likelihood of informed action [28]. Unlike conventional data presentation, data storytelling incorporates context, interpretation, and meaning, thereby extending beyond the mere display of numerical information. By combining analytical results with visual elements and creating a narrative, data storytelling seeks to communicate insights and bridge the gap between different stakeholders, enabling a shared understanding across technical and non-technical audiences.

To enhance understanding, engage the audience, and bridge the gap between data and action, effective data storytelling requires a clear awareness of the target audience, a focus on key insights, the use of appropriate and compelling visualizations, and the construction of a intelligible narrative [28]. Equally important is maintaining honesty and transparency in the presentation of data. Common pitfalls, such as information overload or the use of misleading or poorly designed visualizations, should be carefully avoided, as they may hinder interpretation and undermine trust.

In the context of this project, these principles will be systematically considered and examined. Insights gained from this work may inform future initiatives aimed at improving data communication practices within healthcare organizations, including hospitals and industry stakeholders such as Mölnlycke.

2.6.2 Process Mining

Process mining is a technique meant to improve processes by discovering and monitoring readily available data from information systems [29]. By extracting data from event logs, clear visual maps can be created, such as flow charts. These maps are then studied to reveal inefficiencies such as bottlenecks, unproductive variants, and deviations from intended design [30]. It is done in three forms: discovery, conformance checking, and enhancement [29]. Discovery focuses on identifying new ways to understand a process without relying on prior models or assumptions. Conformance checks whether the process operates as intended by comparing the actual event log data with an existing process model. Enhancement uses information from event logs to extend or improve an already existing model, making it better reflect the real process.

2.6.2.1 Data Requirements

By implementing process mining, workflows can be optimized. However, in order for process mining to be applicable in the perioperative workflow, the underlying event data that is provided needs to be accurate and held at a high quality. This could then serve as a future basis for prediction and decision support [29].

In order to apply process mining, there are a few minimum requirements [31]. First there needs to be an activity, this could be anything from a payment taking place to a specific event happening. Next there needs to be a timestamp indicating when the activity takes place. The last thing needed is a resource, an ID unique for the specific activity. By including these three parameters, it is possible to separate and visualize each of the event flows.

3
Methods

This chapter describes the methodological approach adopted in this thesis. It outlines the overall research design, the data sources, the analytical methods applied, and the procedures used to evaluate and present results. The methodology is designed to support systematic, transparent, and reproducible investigation of material-related surgical workflows using data-driven techniques, while accounting for the constraints of data availability and practical feasibility within a healthcare context.

3.1 Research Design

The study combined empirically collected observational data from a hospital-based shadowing study with qualitative data from interviews conducted at the hospital. The empirical data was used to define, parameterize, and check the stimulated workflow behavior prior to analyzes, and the qualitative data was used to complement the missing data, as well as providing more knowledge about the surgical workflow to the authors.

Given the limited accessibility of real-world clinical data and the early, conceptual nature of the investigated solution, the study followed an exploratory research design [32]. The work was focused on analyzing structured operational data to identify patterns, inefficiencies, and improvement opportunities within surgical material workflows.

The data provided was only regarding the picking process. As mentioned in the Theoretical Framework, Section 2, this is the part of the surgical workflow that has been identified containing most bottlenecks, delays, and interruptions.

3.2 Literature Review

A literature review was conducted to identify research related to healthcare workflows, OR logistics, process mining applications in healthcare, and analytical methods for workflow analysis. Scientific literature was primarily identified through the academic databases PubMed and Google Scholar.

The search strategy combined keywords related to healthcare workflows and operational processes with methodological terms such as process mining and model validation. Additional sources were identified through reference lists of relevant publications and methodological textbooks. The databases and search strategy are summarized in Table 3.1.

The selection focused on peer-reviewed journal articles and academic books relevant to workflow analysis in healthcare environments and hospital operations. Priority was given to recent studies providing empirical insights into workflow optimization, with particular emphasis on research conducted in Nordic and Western European healthcare settings to ensure contextual relevance.

Titles and abstracts were screened to assess relevance, and studies not directly related to workflow processes, OR logistics, or analytical methods were excluded. In particular, studies focusing primarily on patient flow rather than operational workflow were omitted. Articles of the remaining studies were then assessed for eligibility, resulting in the final set of literature included in the theoretical framework.

In addition to academic literature, internal reports and background materials provided by Mölnlycke were used to support contextual understanding of surgical workflows and the operational environment.

Table 3.1: Databases and search strategy used for the literature review

Sources searched	Search terms
Peer-reviewed literature • PubMed • Google Scholar	(“healthcare workflow” OR “picking material in healthcare” OR “picking process OR nurses” OR “operating room workflow” OR “perioperative workflow” OR “hospital logistics” OR “surgical preparation” OR “workflow interruptions” OR “operating room efficiency”) AND (“process mining healthcare” OR “process mining hospital” OR “model validation”)
Additional sources • Reference lists of relevant publications • Methodological textbooks (qualitative methods, interview methods)	Supplementary searches based on relevant keywords and concepts identified during the review process
Contextual material • Internal reports and background material from Mölnlycke	Used for contextual understanding of surgical workflows

3.3 Data Sources

The primary empirical data source for this thesis was a hospital-based shadowing study of OR workflows. The shadowing data captured observational measurements and structured notes related to the picking and preparation processes, handling activities related to materials, and workflow interruptions. Since the data from the shadowing study was partially incomplete, interviews at the same department were conducted in order to fill in the gaps of missing information. No identifiable patient data were used at any stage of the project.

3.3.1 Shadowing Study

The shadowing study was conducted in 2024 at a hospital in Sweden and involved two observers following the OR workflow with a particular focus on interruptions experienced by healthcare personnel. Although the primary objective of the study was not to collect data specifically for later future data-driven analysis, it yielded a substantial amount of observational information that could be leveraged to inform subsequent workflow analysis.

The study spanned five days and documented 24 individual workflows. Although participants were not explicitly instructed to alter their behavior, the presence of observers during data collection may have introduced a degree of behavioral modification, consistent with what is commonly referred to as the Hawthorne effect [33], potentially affecting the frequency and nature of recorded interruptions. To increase transparency and contextualize such subjectivity, background information such as the experience level of the involved nurses was recorded, particularly for variables related to perceived complexity.

The study captured a wide range of variables that could be translated into data points, including type of surgery, complexity of picking, experience level of the picking nurse, total time spent picking materials, time spent transporting items, number of items picked, time spent searching for information using different sources such as scheduling-systems or other colleagues, waiting time during the picking process, number of interruptions, reasons for interruptions, and additional qualitative observations.

3.3.2 Interviews

To complement missing or incomplete observations in the shadowing dataset, qualitative interviews were conducted with hospital staff at the same department as the shadowing study. The interviews served as a complementary data source to the quantitative workflow data provided by the shadowing study. Their purpose was to provide contextual insights into the perioperative workflow and to support the interpretation of event-based workflow data.

According to Lantz [34], an important aspect of qualitative interviewing is maintaining quality awareness in both the design and execution of the interview. This involves careful preparation to ensure that questions are formulated in a way that reduces the risk of over-interpretation or confirmation bias. As part of the preparation process, a pilot interview was conducted with one of the individuals from Mölnlycke involved in the shadowing study, in order to evaluate the clarity and relevance of the interview questions.

Qualitative interviews involve interpretation of both the questions and the responses, which requires balancing structure and flexibility. Lantz [34] distinguishes between three primary interview formats: open, structured, and semi-structured interviews. In this study, a semi-structured interview format was chosen. This format allows predefined thematic areas to guide the conversation while still enabling participants to elaborate on their experiences and perspectives. Semi-structured interviews are commonly used when collecting information from key informants who possess practical experience and contextual knowledge related to the topic of the study [35].

The semi-structured format was particularly appropriate for this thesis, as it allowed the interviewees to describe how material preparation, missing items, or rescheduling of surgeries affect the daily workflow in practice. These contextual insights helped interpret the quantitative workflow data and provided a better understanding of how operational disruptions propagate throughout the surgical workflow.

Following recommendations by Galletta [36], the interview design was structured into three phases: an opening phase to establish a level of comfort and introduce the topic as well as asking for permission to record the conversation, a middle phase focusing on the main thematic questions, and a concluding phase allowing participants to reflect on the discussed topics. The interviews followed established qualitative research guidelines including defining the study purpose, identifying participants, developing an interview guide, conducting the interviews, and documenting reflections for subsequent analysis [35].

The interview guide used during the study is provided in Appendix A.

3.3.2.1 Participants

Participants were selected through purposive sampling in collaboration with hospital contacts to ensure representation of key operational roles within the surgical workflow. The purpose of the sampling strategy was not statistical representativeness but rather to obtain informed perspectives from individuals with practical experience of the workflow processes under investigation.

Three separate interviews were conducted with three different participants involved in the perioperative workflow at the hospital. They were all OR nurses with different amount of experience in the perioperative workflow. Firstly a nurse with twelve years of experience was interviewed. It was clear that this interview-object had seniority and experience over many of their peers. It was also in this nurses work description that they would be in charge of material-handling, and procedure cards.

The two other participants had two and eight years of experience, respectively. The interviews were complemented with a tour of the department.

The most experienced OR nurse interviewed were asked questions regarding the shadowing study, hence their experience at the department but also their experience with being responsible for the procedure cards. The goal was to fill in the gaps of missing data from the shadowing study.

3.3.2.2 Procedure

The interviews were carried out in March and April of 2026. The interview-guide ensured that all participants were asked about comparable themes related to material preparation, workflow coordination, and operational disruptions within the perioperative process.

Each interview lasted approximately one hour and was conducted on-site at the hospital. During the interviews, notes were taken and reflections were documented immediately after each session to support subsequent analysis. Participation was voluntary and participants were informed about the purpose of the study.

3.3.3 Survey

A survey was designed to capture healthcare staff's perceptions of digitalization in the preoperative workflow, with a particular focus on the material picking process. The survey aimed to get a greater understanding of the healthcare personnel's insights and opinions regarding digitalization in healthcare. The target group consisted of OR staff at the department where the shadowing study and interviews were conducted.

3.3.4 Synthetic Data

Following the interviews, not all missing data points could be satisfactorily resolved. Consequently, synthetic data were used to address these gaps. The generation of synthetic data was informed by insights obtained from the interviews, ensuring that the data were grounded in domain knowledge. Where applicable, iterative imputation was used as a way to generate the missing values. Iterative imputation is a multivariate imputation strategy that utilizes all values in a dataset as a means for predicting new values to fill in the gaps [37].

3.4 Data Processing

This section describes the steps taken to prepare and analyze the collected data. The process included data quality assurance and analytical methods. Further, the data was analyzed utilizing techniques such as: correlation matrices, multivariate regression, variance inflation factors, and residual analysis. These methods were used to validate that the data was meaningful and could be used for analysis.

3.4.1 Data Quality

Ensuring high data quality is essential for conducting credible analyzes [38]. This requires that the underlying data are consistent, comparable, and accurately represent the observed processes.

To achieve this, the data were standardized to ensure uniform formats and definitions across all variables, enabling meaningful comparison and analysis. In addition, descriptive statistics and exploratory data analysis were applied to identify inconsistencies, outliers, and potential data quality issues.

The dataset obtained from the shadowing study was complemented with data from the interviews, resulting in the integration of multiple data sources. To ensure that the combined dataset was coherent and reliable, measures were taken to align variables and resolve inconsistencies, enabling seamless data integration [39].

3.4.2 Descriptive Statistics and Statistical Soundness

The first step of the validation was to ensure the statistical soundness of the dataset. Since the dataset was in a complete case there was no need to look for missing values, instead the first step was to visualize the different data points in order to establish that all the data types were coherent and could be compared and used for further analysis. The data was visually inspected. Both by extracting the descriptive statistics but also visual plots that described the different flows. This way outliers and statistical anomalies could be detected and dealt with accordingly.

The following parameters were analyzed in order to establish the soundness of the dataset: Counts, datatype, mean, standard deviation, and variance.

3.4.3 Correlation Matrices

Correlation matrices maps the relationship between the features of the data. By calculating a correlation coefficient, between negative one and one, the relationship between two variables can be explained, where zero indicates that there's no correlation. A value of one means that an increase in the one variable increases the other, likewise a negative one means that an increase in one variable leads to a decrease in another. This is an effective method to see which variables have strong relationships and can show if there's any multicollinearity, which would distort parameters for regression models [40].

3.4.4 Regression Analysis

Regression analysis, or in this specific application multiple linear regression, models the relationship between two or more variables and how they affect another single metric by trying to fit linear equations to the variables [41]. This analysis is guided by questions, and for this thesis the following guiding questions have been asked:

- How does the experience of the picker, the complexity of the pick, and the number of interruptions effect the picking time?
- How does the experience of the picker, the amount of items picked, and the complexity of the pick effect the number of interruptions?
- How is the total time spent searching for information affected by the perceived complexity, the type of surgery, and the experience of the user?

By answering these questions, hopefully insights will be gained in the relationship between perceived complexity, experience, and how often interruptions occur in the workflow. Multiple linear regression could also be used to answer wether variables can be used for pattern and trend prediction, by explaining the variations in the relationships among variables which in turn can be used for future estimation [41].

3.4.5 Variance Inflation Factor Analysis

The Variance Inflation Factor (VIF), indicates to what degree a regression coefficient is increased based on multicollinearity among the variables [42]. Multicollinearity determines wether independent variables in a linear regression model are correlated, this could affect models negatively especially when it comes to predict new values on unseen data [43]. According to Marcoulides [42], values over five or in some cases ten, could contribute to multicollinearity, causing problems with linear models. By including these variables in the analysis, relevant predictors could potentially be missed as an direct effect of multicollinearity. Proposed solutions to variables with a too high VIF, is to either replace or remove them.

3.4.6 Residual Analysis

Residual analysis is a technique to determine how well a model fits to the data. By comparing the differences between predicted and observed values, it is possible to answer how well the model is based on it's accuracy, reliability, and ability to capture patterns. By plotting the residuals with a horizontal baseline it is possible to identify outliers, and patterns. The presence of patterns indicates that the model is inadequate which might be caused by a simplistic model [44].

3.5 Process Mining

Process mining has emerged as a prominent method for analyzing healthcare processes by leveraging event logs that describe how workflows are executed in practice. By reconstructing sequences of activities, these techniques can reveal bottlenecks, deviations from clinical guidelines, and inefficiencies in both clinical and organizational processes [12]. However, existing applications of process mining in healthcare are largely limited to specific case studies and rely heavily on structured and well-documented data. In practice, many activities within healthcare workflows are either inconsistently recorded or not captured at all in hospital information systems. As a result, certain components of the perioperative workflow remain invisible in data-driven analyzes. On top of that, a large part of the process mining performed focuses on costs and patient-flows, and not the perioperative flow for the healthcare personnel.

Process mining was applied to the data utilizing a python library called PM4PY [45]. It is an open source process mining library used under an academic license. The library offers a wide range of applications and analysis for event-data.

In order for the process mining to be applied, the structure of the data had to be changed. Instead of tabular data describing the 24 separate flows, the data was translated to event data. For each event, such as the picking process, new timestamp-variables were created, indicating both start and end of the process. These new variables were labeled as a type of activity corresponding to a specific timestamp. Since the focus lies on optimizing the picking flow, all interruptions were infused between the variables indicating start and finish. This resulted in a flow chart describing the flow of the operations, that laid the foundation for further visual analysis. Since the data had to be transformed, the dataset containing the event logs became purely theoretical as the infused interruptions are synthetic.

3.6 Dataset

The dataset used in this study was generated through the shadowing study of the picking process, resulting in a total of 24 recorded workflows. The variable names and their descriptions can be found in Table 3.3. The completeness of the dataset varied across variables. Fully captured variables included the total duration of the picking process and interruption-related measures, such as number of interruptions (`NRINTER`), transportation time (`TOTTRANS`), and total interruption time (`TOTINTER`). Along with these variables the date and times were all collected, referred to in this dataset as (`TIMESTAMP`).

The recorded item data exhibited inconsistent notation. The items are categorized into four categories: sterile grids, individual items, implant materials found in drawers, and other materials, these are annotated as (`PICKG`), (`PICKI`), (`PICKD`), and (`PICKO`). The study also covered in which OR the surgery was going to be performed in (`OR`), and what type of surgery it was either a trauma or an implant (`SURTYPE`).

Time spent searching for information (`TOTINFO`) was not complete for all the workflows, as well as the waiting time (`TOTWAIT`).

Other variables were also only partially observed. For example, the expected complexity of the pick (`COMPLEX`) was not recorded for the first four workflows, resulting in systematic missingness. In addition, inconsistencies in the description of surgical procedures required the introduction of a standardized procedure identifier (`SID`) to enable comparative analysis.

Certain relevant variables were not directly available in the dataset and were therefore constructed. The identity of the picker was not recorded, instead an experience-based identifier (`EXP`) was given, where lower values correspond to less experienced staff, ranging from 6 months, to 10+ years. As surgeon information was not available, a synthetic surgeon identifier (`SUR`) was introduced.

By creating an ID for every different surgery, (`SID`), the subsequent analysis was easier going to distinguish the difference in complexity, picking time, or information availability between different types of surgeries. The system created to separate the different surgeries can be seen in Table 3.2:

Table 3.2: Coding scheme for procedure classification

Category	**1**	**2**	**3**	**4**	**5**	**6**	**7**
First number	Trauma	Implant	-	-	-	-	-
Second number	Elbow	Hip	Knee	Foot	Shoulder	-	-
Third number	Radius	Femur	Knee joint	Hip joint	Ankle joint	Ulna	Humerus
Fourth number	Internal fixation	Fracture reduction	Joint replacement	Amputation	Screw removal	Mayo plate	Tissue excision

A surgery could be divided into sub-groups, creating a coding format for each surgery, translating every surgery to a four digit number. For example, an ”Internal fixation of the radius bone” would be 1111, as the radius bone is connected to the elbow and that is classified as a trauma surgery. Another example would be 2243, describing a joint replacement of the hip joint.

Temporal variables for the picking process were defined using start (`SPICK`) and end (`EPICK`) timestamps, from which total picking time (`TPICK`) was derived.

Additional variables related to preparation and surgery phases were generated based on insights from the interviews. Preparation time variables (`SPREP`, `EPREP`, `TPREP`) were modeled based on the number of sterile grids and staff experience, ranging from 20 to 34 minutes. Surgical durations were assigned within a range of 40 to 120 minutes to reflect typical procedure variability.

Table 3.3: Variables of the dataset with their descriptions

Variable name	Description
Timestamp	Timestamp of the picking process
SID	Surgery ID
ID	ID of user
SUR	Active Surgeon
FIRSTS	First surgery of the day
OR	Operation room
SURTYPE	Type of surgery (Trauma/Implant)
SPICK	Start of picking process
EXP	Experience of the user
COMPLEX	Perceived complexity of pick
NRINTER	Number of interruptions during pick
TOTINTER	Total interruption time
TOTINFO	Total time spent looking for information
TOTTRANS	Total time spent transporting
TOTWAIT	Total time spent waiting
PICKG	Picked grids
PICKI	Picked single items
PICKD	Picked drawers
PICKO	Picked other
EPICK	End of picking
TPICK	Total time spent on picking
SPREP	Start of preparation
EPREP	End of preparation
TPREP	Total time spent on preparation
SSURG	Start of surgery
ESURG	End of surgery
TSURG	Total time spent on surgery

4

Results

This chapter presents the empirical findings from the interviews and the shadowing study. The results are structured in two main parts. First, the interview findings are presented thematically, focusing on material preparation challenges, workflow disruptions, information access, and rescheduling. Second, the shadowing study dataset is presented and analyzed through descriptive statistics, visualizations, correlation analysis, regression analysis, and process mining. Given the exploratory nature of the study and the limited size of the dataset, the results should be interpreted as indicative rather than statistically generalizable.

4.1 Findings from Interviews

This section presents the findings from the semi-structured interviews conducted with OR nurses. A thematic analysis approach was applied to identify recurring patterns and perspectives across participants. The findings are structured into key themes reflecting challenges, workflow disruptions, and information-related aspects of the material preparation process.

4.1.1 Complementary Data

The interviews were conducted to complement gaps identified in the shadowing study data, as described in Section 3.6. Specifically, several variables, such as `(COMPLEX)` and `(TOTINFO)`, were not captured in full in the dataset.

Participants were able to provide expert-based assessments of these missing variables. In particular, the highly experienced OR nurse, with several years of involvement in the material preparation process, provided consistent evaluations of picking complexity. These assessments were based primarily on information availability and the number of sterile grids required for a given procedure. The participant expressed a high level of confidence in these evaluations, indicating that such factors are reliable determinants of complexity in practice. This allowed for approximate classification of picking complexity across process types not represented in the dataset.

More broadly, the interviews provided insights into the relationships between different stages of the workflow and how tasks interact in practice. Participants also reported similar estimates regarding the frequency of interruptions and waiting times during the picking process, indicating a level of consistency across responses.

4.1.2 Material Preparation Challenges

The material picking process was described as complex and context-dependent. While procedures may involve many instruments, complexity was primarily driven by incomplete, unclear, and fragmented information.

Participants reported relying on multiple information sources, as procedure cards were often insufficient. This required additional communication or the use of approximations, increasing the risk of inaccuracies.

Logistical factors further contributed to inefficiencies, as materials were distributed across multiple locations and not always clearly documented. Missing items were also a recurring issue.

Experience was identified as a key factor in managing these challenges, with more experienced nurses relying on tacit knowledge, while less experienced staff reported greater difficulty. As a result, the process was difficult to standardize.

One of the identified headaches from the interviews is that material is often missing or misplaced, which in turn leads to delays and further interruptions. There are also instances where a material is double booked, where two surgeries require the same material during the same day, in these cases either rescheduling, new material needs to be found or the sterile center needs to prioritize. It also became apparent that surgeons tend to plan their surgeries according to what material that they have at hand. Meaning that because they think they can use one set of material they plan the surgery based on that material, where they in practice could have used another technique had they known about the specific material shortage of the first technique.

4.1.3 Interruptions and Workflow Disruptions

Interruptions were described as a frequent and impactful component of the material picking process. All participants reported being interrupted during picking, either by colleagues seeking assistance or by the need to actively search for missing information. The frequency of interruptions varied depending on factors such as time of day, workload, and level of experience, but was commonly reported to occur at least once per picking process, and in some cases up to several times.

Experienced nurses were more likely to be interrupted by others due to their role as informal knowledge sources within the department. At the same time, less experienced nurses reported a higher need to interrupt others in order to obtain necessary information, reinforcing a cycle of dependency within the workflow. Additionally, interview responses suggest that interruptions after a completed surgery or shift are generally perceived as undesirable. Participants are unlikely to welcome additional demands such as answering questions, completing forms, providing qualitative feedback, or reviewing performance metrics, after just finishing a long surgery. For this reason, any requests for feedback should preferably be integrated into the active workflow, or during administrative hours.

Interruptions were consistently described as disruptive to both efficiency and quality. Participants emphasized that it could be difficult to resume the picking process after an interruption, particularly in complex cases involving many instruments or multiple information sources. This often resulted in repeated checks or uncertainty regarding whether all required items had been collected.

In addition to direct interruptions from colleagues, participants highlighted structural disruptions such as waiting for sterile instruments or the information systems, caused by limited access to the department's shared computer. Waiting for sterile instrument trays was identified as a particularly common source of downtime, often creating bottlenecks in the workflow.

Overall, interruptions and workflow disruptions were identified as a key factor contributing to inefficiencies in the picking process, affecting both time consumption and cognitive workload.

4.1.4 Information Fragmentation

A recurring theme across all interviews was the fragmented nature of information within the workflow. Participants described the need to continuously switch between multiple systems in order to retrieve the necessary information for a single picking process as different systems contain different information. As sensitive patient information could be present in these systems, every nurse has to log in and log out every time they use the computer, a time consuming activity the interviewees complained about.

An additional issue related to information fragmentation was the lack of visibility of material demand across departments. Participants described situations where the same instruments or implants were required for multiple procedures, without this being clearly reflected in the system. As a result, materials could be unintentionally allocated to one operation while being simultaneously needed for another, creating conflicts in resource availability.

This lack of coordination across departments required manual intervention, such as contacting the sterilization department or re-prioritizing materials between procedures. In some cases, the issue was not identified until late in the workflow, leading to delays or last-minute adjustments.

Another contributing factor to information inefficiency was the distribution of responsibilities across different roles in the workflow. Participants described that the picking, preparation, and surgical phases could be handled by different OR nurses, in the same surgical workflow. Due to limited communication and lack of shared, structured information, this can lead to repeated information gaps. In practice, this resulted in multiple nurses independently contacting the surgeon to clarify the same details at different stages of the workflow. One example from the interviews, stated that the picking-nurse sees that an item is missing and therefore calls the surgeon to discuss which replacement should be used. When a different nurse, in charge of the preparation, sees that a different item is used, they call the same surgeon to confirm the usage of this item instead. The third OR nurse involved in the workflow calls the surgeon again before the surgery when a final pre-surgery count is underway. This is one clear example where the interviewees indicated that improved information sharing between workflow stages could significantly reduce repeated communication.

Several participants highlighted that unclear or inconsistent terminology used by surgeons and other departments further complicated the information retrieval process. This sometimes required additional clarification, including phone calls, to ensure that the correct materials were selected. In some cases, even surgeons were reported to be uncertain about specific instrument requirements, further increasing the need for iterative information seeking.

The lack of integration between systems, combined with inconsistent information quality, contributed to inefficiencies and increased the likelihood of errors or duplicated work. The complexity and non-linear nature of the workflow described by participants is illustrated in the example process map created, found in Figure 2.3.

4.1.5 Impact of Reschedules

Rescheduling of surgeries was described as a frequent occurrence that could occur at any stage of the workflow, including during or after the picking and preparation phases. This unpredictability made it difficult to plan and prioritize tasks effectively. Participants reported that information about cancellations or rescheduling sometimes does not reach them in a timely manner, and in some cases is not communicated at all. This resulted in situations where materials had already been picked or prepared for procedures that were subsequently canceled.

The consequences of rescheduling included additional workload, as materials needed to be returned, reorganized, or in some cases discarded. This was described as inefficient and frustrating, particularly when preparation had already been completed. In addition, rescheduling required rapid adjustments to the workflow, often under time pressure, which further increased the risk of errors.

Overall, the lack of structured and reliable communication regarding schedule changes was identified as a major source of inefficiency and unnecessary work within the perioperative workflow.

4.1.6 Updated Process Map

The interviews provided a more comprehensive understanding of the perioperative workflow, particularly how different processes and staff roles interact. As outlined in the Theoretical Framework, Section 2.1, the perioperative workflow consists of three primary flows: surgical, material, and patient flows. In this study, the patient flow is not explored in detail. The interaction between these flows is illustrated in Figure 4.1.

The surgical flow, displayed above the dotted line, is illustrated using yellow and orange shapes. The material flow, shown below the dotted line, is represented by blue boxes and circles. The boxes are meant to represent events, whereas the circles represent different kinds of items. Rescheduling events are depicted as red rhombuses and may occur throughout the entire preoperative phase. Dashed lines connect the different flows, indicating that they are the same rescheduling events, illustrating how reschedules can propagate across both workflows.

The time axis begins when the patient enters the system, typically at admission or when surgery is scheduled, and ends upon patient discharge. Within the surgical workflow, orange rhombuses represent material-related disruptions, such as missing, incorrect, or contaminated items. These events may trigger a return to earlier stages, particularly the picking phase.

An enlarged version of Figure 4.1 is provided in Appendix C.

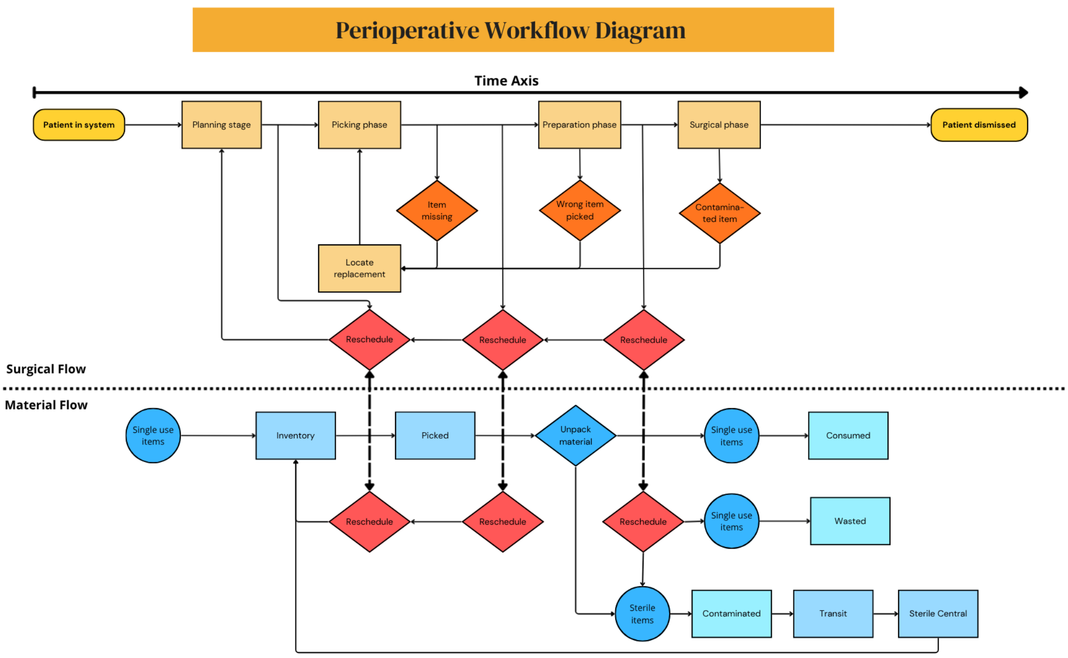

Figure 4.1: A process map of the perioperative workflow as a combination of the surgical and material workflow

4.2 Data from the Shadowing Study

This section presents the quantitative data obtained from the shadowing study and the analyzes performed to explore patterns in the picking process. The purpose is not to draw statistically generalizable conclusions, but to examine how the available workflow data can be structured, visualized, and analyzed to support interpretation of interruptions, time distribution, and procedural variability. The section begins with an overview of the dataset and its descriptive statistics, followed by exploratory statistical analysis, visual representations of the workflows, and process mining outputs.

Table 4.1 provides an overview of the dataset, containing the numerical variables used for subsequent analysis and visualization. The full dataset is provided in Appendix D.

The variables shown are described in Section 3.6. The variables are measured in minutes for time-related variables (denoted by the prefixes `TOT` or `T`), counts for item-related variables and interruptions, and on ordinal scales from 1-5 for both complexity and experience.

Table 4.1: Overview of the complemented shadowing study dataset, presenting recorded variables for each workflow

Workflow	COMPLEX	EXP	NRINTER	TOTINTER	TOTINFO	TOTTRANS	TOTWAIT	PICKG	PICKI	PICKD	TPICK	TPREP	TSURG
0	3	1	2	2	11	2	4	5	14	0	60	26	80
1	2	1	2	2	5	1	2	3	5	1	12	28	116
2	4	2	0	0	10	1	0	2	7	1	14	22	52
3	3	1	0	0	9	1	3	2	4	1	14	25	87
4	2	4	1	5	1	4	1	8	9	2	18	26	95
5	2	4	1	5	1	4	1	10	9	1	19	21	35
6	3	2	1	1	0	5	0	0	0	3	7	25	97
7	4	2	0	0	0	6	4	0	0	3	11	21	49
8	2	2	0	0	1	2	1	2	5	0	9	21	37
9	5	1	0	0	27	25	6	18	17	5	76	34	134
10	2	3	0	0	2	1	1	1	7	2	5	29	136
11	3	3	1	2	6	1	5	3	10	2	16	28	119
12	2	3	2	3	1	1	1	3	5	0	9	23	64
13	2	5	2	2	7	3	0	4	11	0	15	20	41
14	3	2	1	2	2	1	2	6	9	2	15	28	105
15	2	2	2	2	2	3	0	2	9	0	8	24	78
16	2	3	1	2	1	2	1	9	6	0	11	22	43
17	3	3	1	2	6	2	3	3	13	1	14	24	84
18	3	2	1	2	3	1	1	5	7	1	8	21	34
19	2	4	3	20	9	2	3	4	5	6	38	28	130
20	2	5	1	1	5	2	1	8	6	0	13	22	58
21	3	4	1	2	6	1	3	4	12	3	14	26	103
22	2	5	1	2	1	1	1	3	5	0	11	21	64
23	2	4	2	3	2	1	0	4	7	0	7	25	87

4.2.1 Statistical Representation of Data

In the statistical representation of the data, the data from the shadowing study was explored, more precisely the numerical variables. These include `COMPLEX`, `EXP`, `NRINTER`, `TOTINTER`, `TOTINFO`, `TOTTRANS`, `TOTWAIT`, `PICKG`, `PICKI`, `PICKD`, `TPICK`, `TPREP`, and `TSURG`. All values can be found in Table 4.2.

Table 4.2: Descriptive statistics of variables from the shadowing study

	COMPLEX	EXP	NRINTER	TOTINTER	TOTINFO	TOTTRANS	TOTWAIT
count	24.000	24.000	24.000	24.000	24.000	24.000	24.000
mean	2.625	2.833	1.083	2.500	4.917	3.042	1.833
std	0.824	1.308	0.830	3.978	5.785	4.885	1.685
variance	0.679	1.710	0.688	15.826	33.471	23.868	2.841
min	2.000	1.000	0.000	0.000	0.000	1.000	0.000
max	5.000	5.000	3.000	20.000	27.000	25.000	6.000

	PICKG	PICKI	PICKD	TPICK	TPREP	TSURG
count	24.000	24.000	24.000	24.000	24.000	24.000
mean	4.542	7.583	1.417	17.667	24.583	80.333
std	3.901	4.021	1.640	16.931	3.425	32.819
variance	15.216	16.167	2.688	286.667	11.732	1077.101
min	0.000	0.000	0.000	5.000	20.000	34.000
max	18.000	17.000	6.000	76.000	34.000	136.000

4.2.2 Data Analysis

This section presents the analytical results derived from the dataset, focusing on exploring relationships between variables and patterns in the picking processes.

To investigate potential relationships, correlation analysis was applied. In Figure 4.2, the correlation matrix of all variables from the shadowing study is displayed. Strong positive correlations can be observed between several time-related variables, such as total picking time, information time, waiting time, and transportation time. These relationships are expected, as total picking time is composed of multiple subprocesses, including information, waiting, and transportation time.

In contrast, experience exhibits negative correlations with several variables, indicating that more experienced staff tend to spend less time searching for information, and the picking process in whole. This suggests that experience may play a role in mitigating workflow inefficiencies.

Overall, the correlation analysis indicates that interruptions and time-related activities are closely interconnected and represent key factors influencing workflow efficiency.

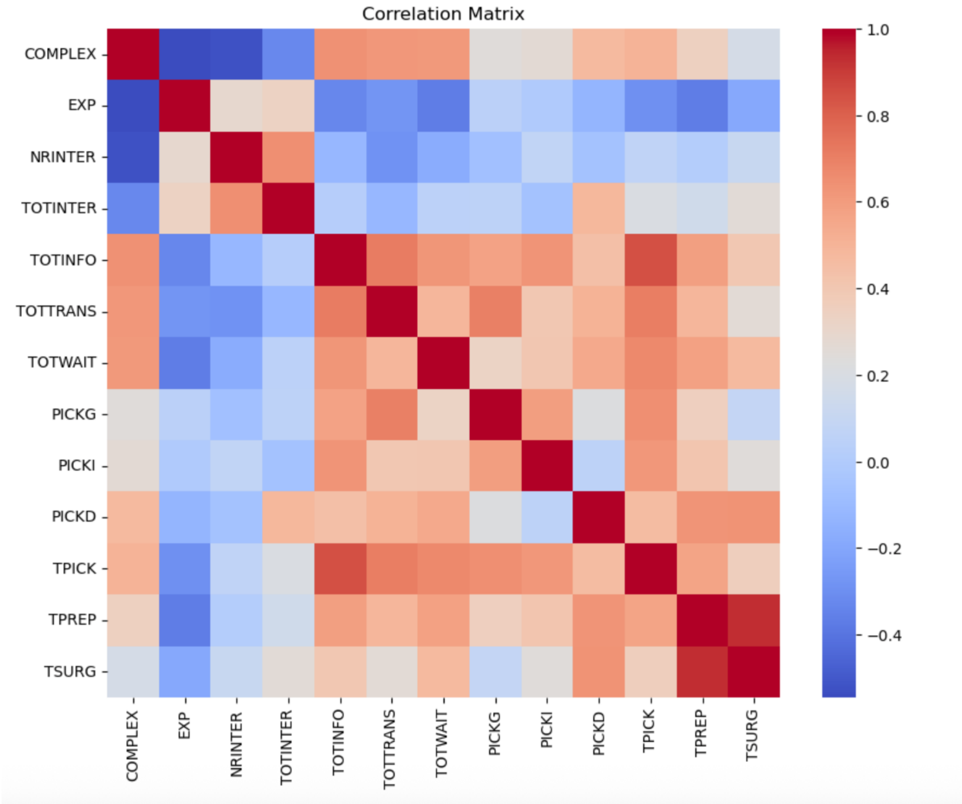

Figure 4.2: A correlation matrix of all variables

As can be seen in Table 4.3, all the variables with their corresponding VIF values are displayed. As mentioned in Section 3.4.5, variables with VIF values > 5, should be used with care, as most likely they could contribute to multicollinearity. Most of the variables indicate a high VIF with only `NRINTER`, and `TOTWAIT` displaying values under five. This should indicate that multicollinearity is a problem present in the dataset.

Table 4.3: Table illustrating the variables and their corresponding VIF

Variable	VIF
COMPLEX	8.310179
EXP	6.981196
NRINTER	3.549729
TOTINTER	11.996858
TOTINFO	6.256734
TOTTRANS	7.438285
TOTWAIT	2.945455
PICKG	11.931846
PICKI	3.369869
PICKD	15.723500
TPICK	8.143055
TPREP	116.152242
TSURG	91.066339

As can be seen in Table 4.4, the following regression analysis were made in order to answer the following questions:

1. How does the experience of the picker, the complexity of the pick, and the number of interruptions affect the picking time?
2. How does the experience of the picker, the amount of items picked, and the complexity of the pick affect the number of interruptions.
3. How is the total time spent searching for information affected by the perceived complexity, the type of surgery, and the experience of the user?

Table 4.4: Regression analysis based on three guiding questions

Question	Dependent Variable	Independent Variables	Adj. R^2	F-stat (p)
1	TPICK	COMPLEX, EXP, NRINTER	0.317	4.555 (0.0137)
2	NRINTER	EXP, PICKG, COMPLEX	0.171	2.577 (0.0824)
3	TOTINFO	COMPLEX, SURTYPE, EXP	0.363	5.370 (0.00707)

During this multiple regression analysis, three components were checked. First the adjusted R-squared value, this component indicates how much of the variance is explained by the model, but accounting for the number of predictors, giving a more conservative estimate of the performance [46]. As can be seen for the three different models, none of them explain the dependent variables very well, that is a score of 0 - 100% [47]. The next components are the F-statistic and the probability of the F-statistic. The F-Statistic assesses the overall significance of the model, where the values indicate wether the independent variable have any effect on the dependent variables. The probability of the F-statistic shows wether the model is statistically significant, with values below 0.05 [46]. From these models it is clear that the first and third question was statistically significant. However, since it is known that the dataset is struggling with a high VIF value and multicollinearity these models can not be taken at face value. This is further strengthened when the individual coefficients are addressed as it becomes quite obvious that the models show significant impact when the coefficients shows the opposite (R-squared value of 31.7, 17.1, and 36.3% respectively), indicating that the models can not be trusted.

The residual plot in Figure 4.3 is used to detect non-linearity, unequal error variances, and outliers. In this case, the residuals are distributed around the zero line, although not entirely randomly, suggesting that the model captures some of the variation but does not fully explain the underlying relationships. Several outliers can be observed, where individual workflows deviate notably from the predicted values. This suggests that certain observations are influenced by factors not included in the model, such as contextual workflow variations or unrecorded disruptions.

Overall, the residual distribution indicates that while the model provides some explanatory value, it does not fully account for the variability in the data. Given the limited dataset, this only emphasizes more that the results should be interpreted with caution.

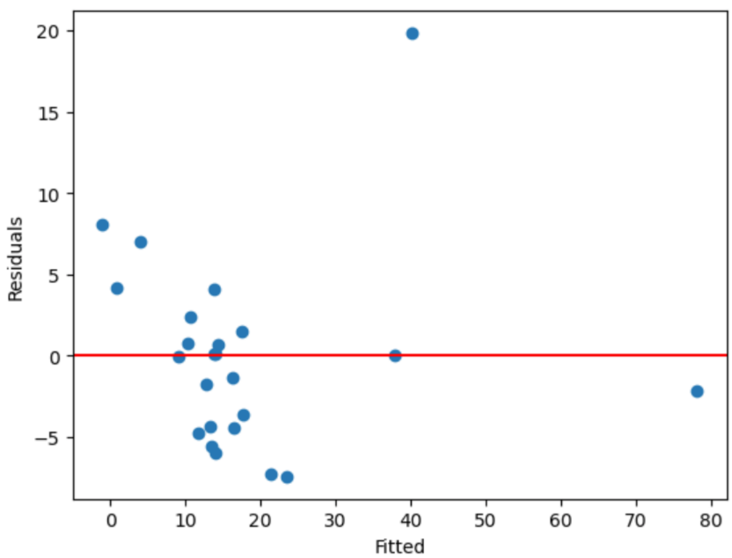

Figure 4.3: Residual analysis of the variables

Figure 4.4 presents the distribution of the numerical variables, illustrating their frequency and dispersion. The visualizations indicate the presence of several outliers across multiple variables, and the distribution shows a high variability in picking time, indicating that the process is not standardized across workflows.

The x-axis represents minutes for time-related variables, counts for item-related variables and interruptions, and ordinal scales from 1-5 for both complexity and experience.

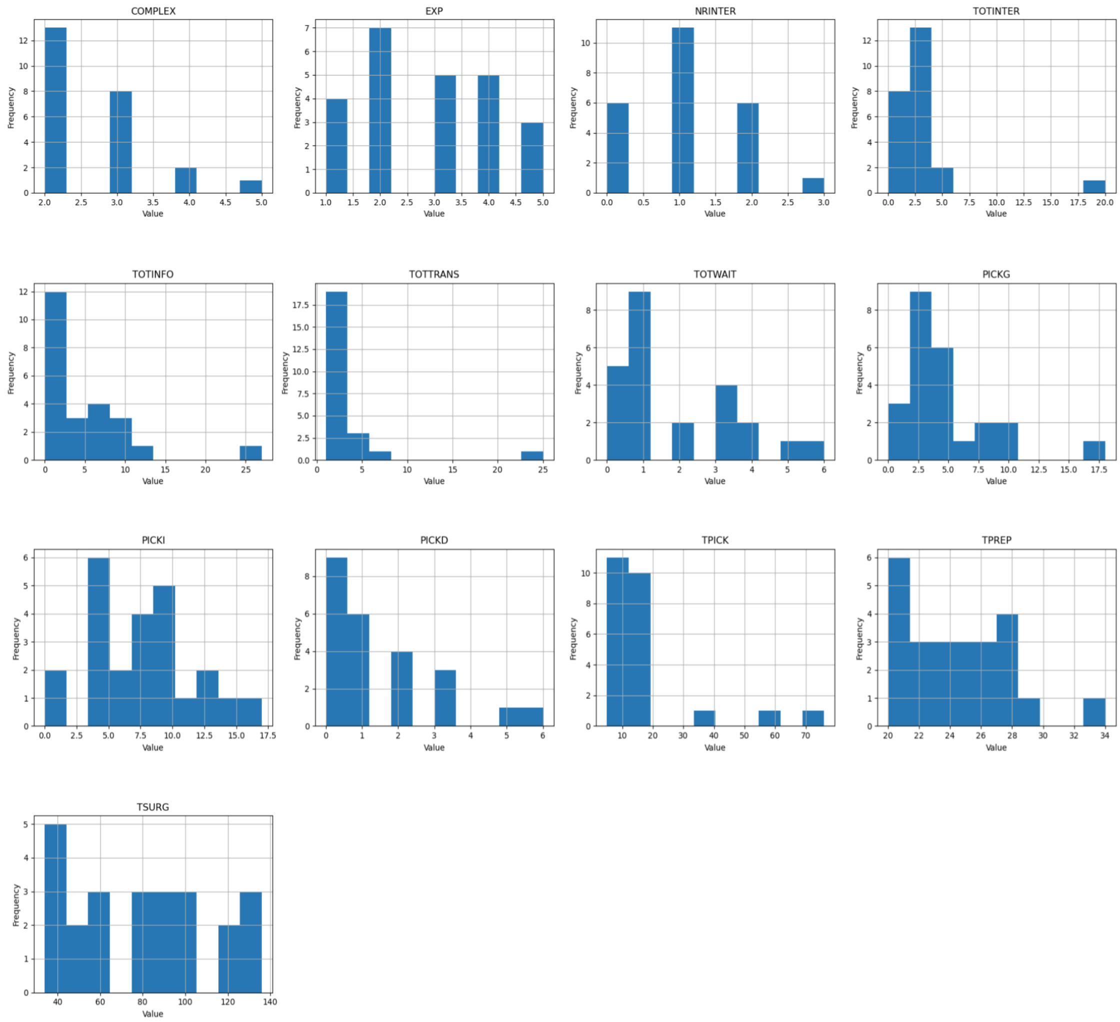

Figure 4.4: A visual overview of the frequency and spread of the different variables

4.2.3 Visual Representation of Data

In Figure 4.5, all the workflows are represented were the y-axis represents the different flows and the x-axis represents time in minutes. The total duration time spans from start of the picking process to the end of the surgery. The image is meant to give an overview of the flows to deepen the understanding and visualize how the flows look.

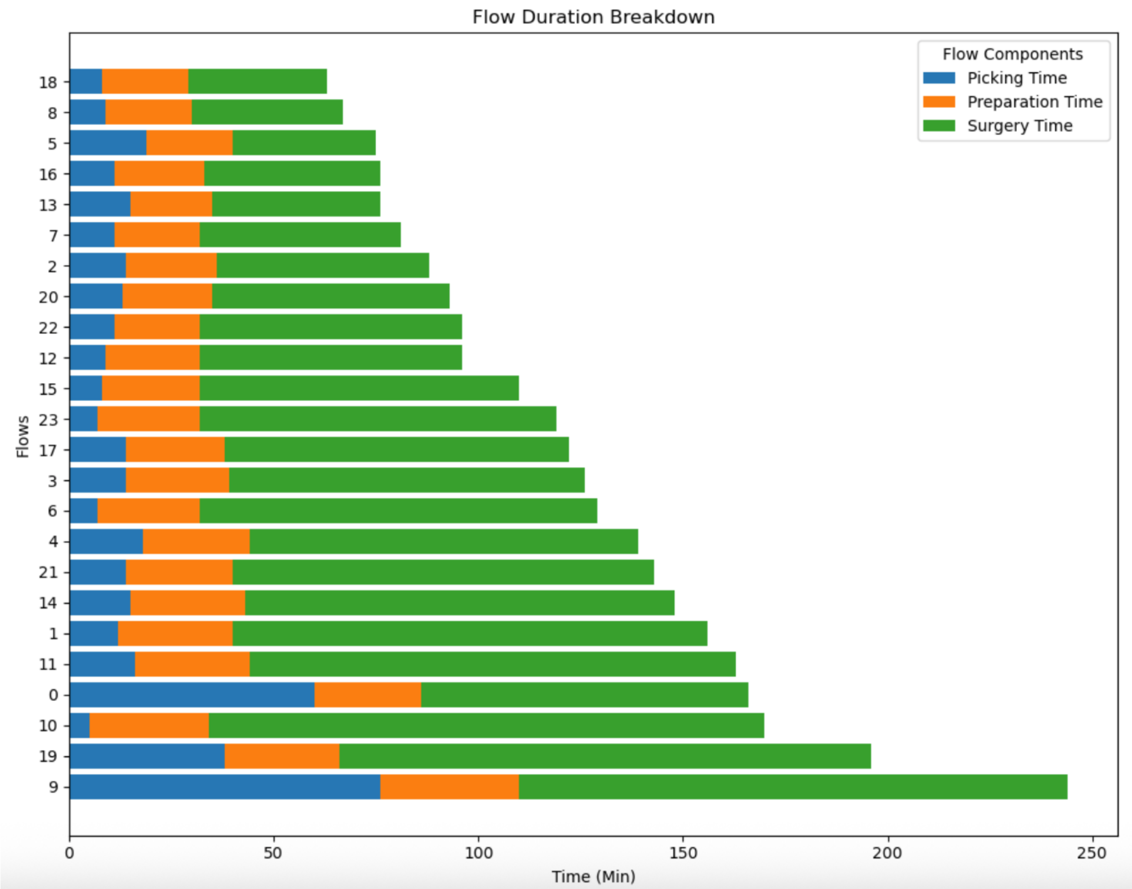

Figure 4.5: Visualizing a breakdown of the 24 different surgical workflows into picking, preparation and surgery time

Figure 4.6 shows the breakdown of the picking process in particular. Since all of the interruptions in the dataset occur in the picking phase, this visual is meant to give an overview of the time allocation during each picking process.

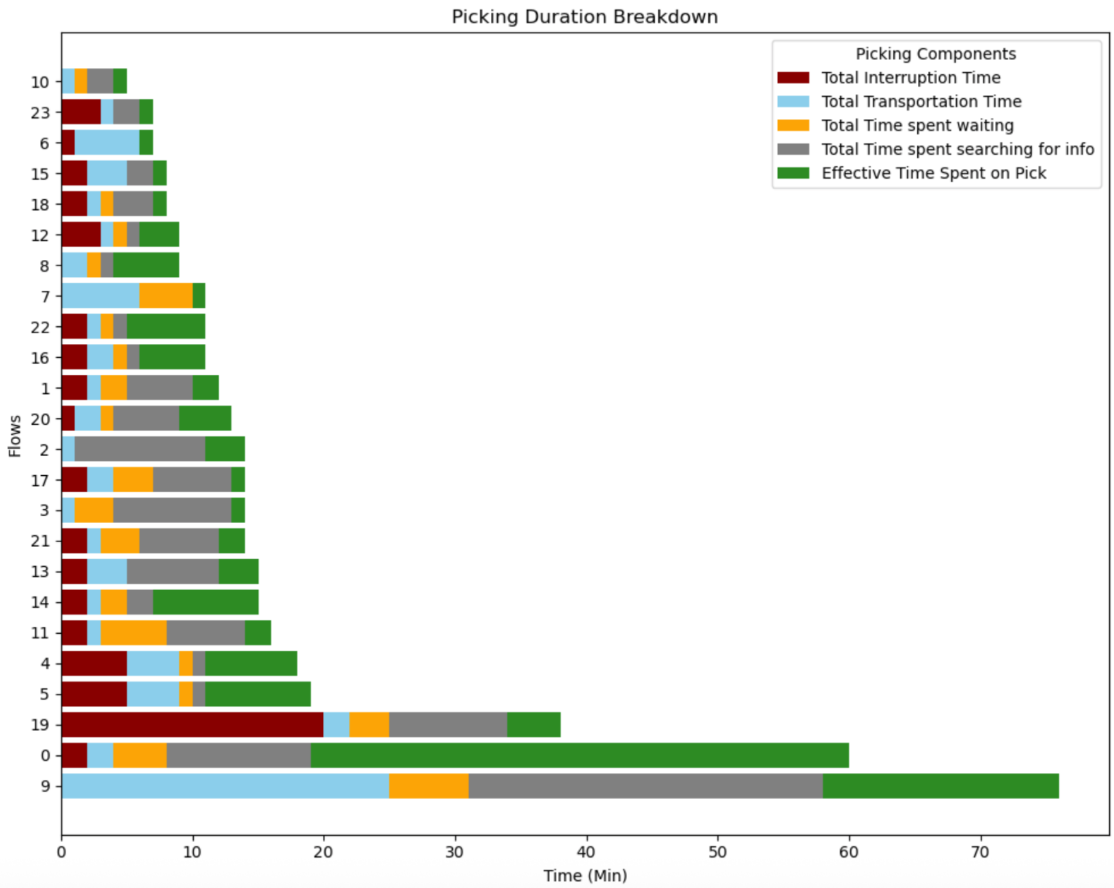

Figure 4.6: Visualizing the 24 different picking processes, breaking down their interruptions

Figure 4.7, provides a breakdown of the total time across all 24 workflows by highlighting the total effective picking time in combination with the total interruption time, time spent waiting, transporting, and information searching.

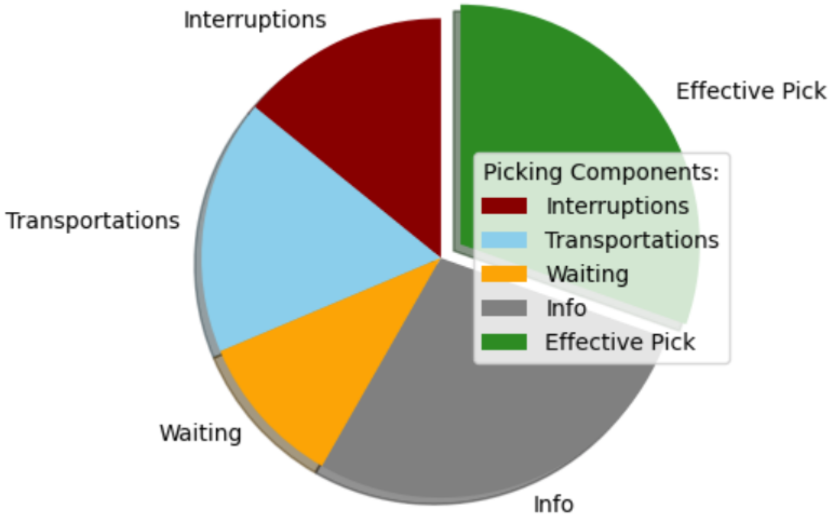

Figure 4.7: A pie chart representing the breakdown of the total time allocation for all 24 picking processes

Each workflow corresponds to a single surgical procedure, and their surgery-ID (`SID`). This allows for the analysis of mean information search time and mean waiting time during the picking process, as illustrated in Figure 4.8.

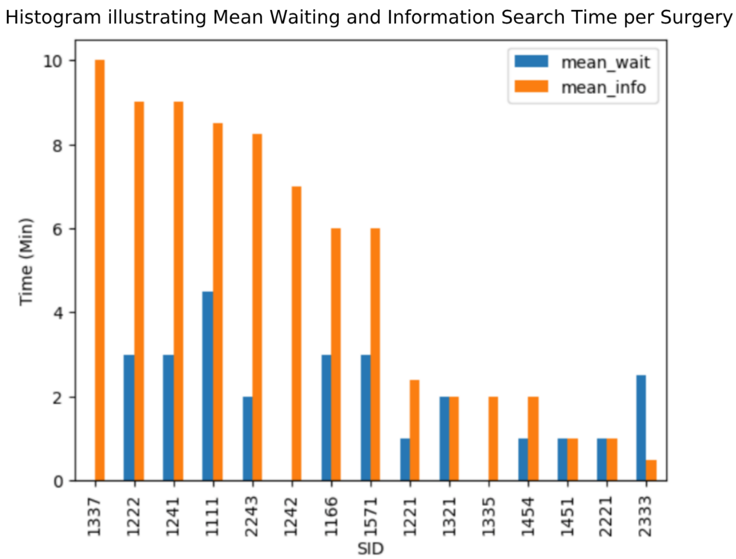

Figure 4.8: A histogram illustrating the mean time spent on information search and waiting time, per surgical procedure

The number of observations per procedure is presented in Table 4.5. It can be observed that many procedures are represented by only a single workflow, which limits the statistical significance of comparisons at the individual procedure level. As a result, the observed variation may be influenced by additional contextual factors not captured in the dataset.

Table 4.5: Mean waiting and information times per surgery and their corresponding frequencies

SID	mean_wait	mean_info	count
1337	0	10	1
1222	3	9	1
1241	3	9	1
1111	4	8	2
2243	2	8	4
1242	0	7	1
1166	3	6	1
1571	3	6	1
1221	1	2	5
1321	2	2	1
1335	0	2	1
1454	1	2	1
1451	1	1	1
2221	1	1	1
2333	2	0	2

By aggregating the data at the level of surgical categories (based on the first two digits of the SID), a higher number of observations per group is obtained. This allows for a more robust comparison between procedure types.

From this grouping, it can be observed in Table 4.6 (and visualized in Figure 4.9) that Trauma-Elbow procedures exhibit a relatively high combined mean time for waiting and information search, amounting to approximately 12 minutes. In contrast, procedures such as Trauma-Foot and Implant-Knee show considerably lower combined times, with mean values of approximately 3 and 2 minutes, respectively.

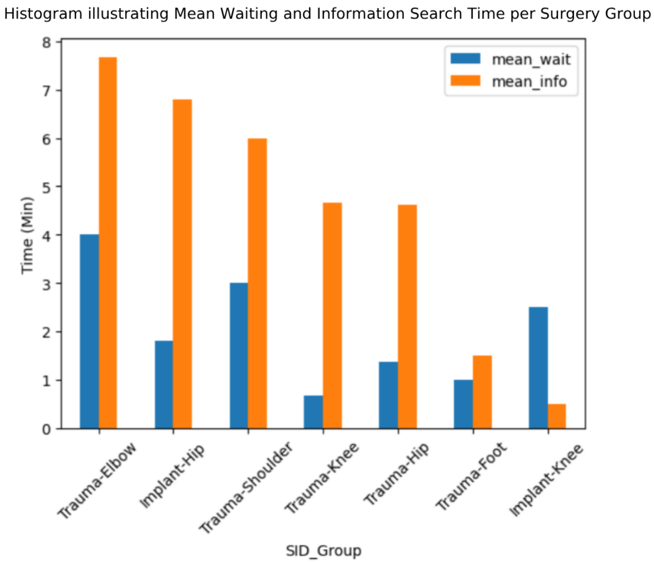

Figure 4.9: A histogram illustrating the mean time spent on information search and waiting per surgery group

Table 4.6: Mean waiting and information times by surgery groups and their corresponding frequencies

SID_Group	mean_wait	mean_info	count
Trauma-Elbow	4	8	3
Implant-Hip	2	7	5
Trauma-Shoulder	3	6	1
Trauma-Knee	1	5	3
Trauma-Hip	1	5	8
Trauma-Foot	1	2	2
Implant-Knee	2	0	2

4.2.4 Dashboard Examples Focusing on KPIs

The following figures, Figure 4.10, 4.11, 4.12, 4.13, 4.14, and 4.15, highlight examples of KPIs that can be extracted in order to gain further insights in the hospital environment. The figures are meant to represent a dashboard solution, highlighting multiple KPIs simultaneously.

The first KPI, Figure 4.10, is illustrating how many surgeries are performed each day, meant to be seen as a monthly overview. However, the collected data from the shadowing study only spans four days.

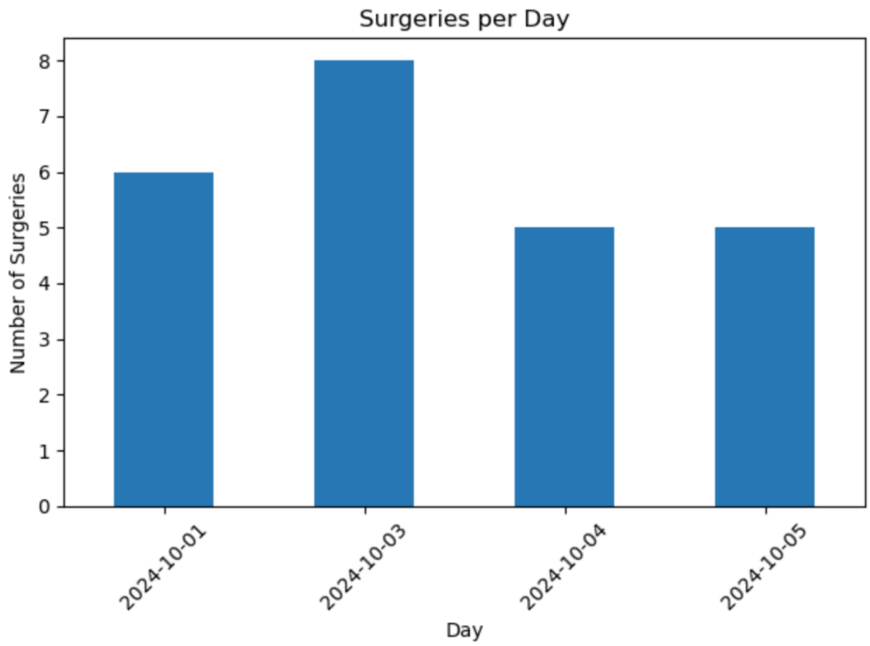

Figure 4.10: A plot visualizing the number of surgeries performed each day of the shadowing study

The second plot shows the average operational times for the picking and preparation process, spanning throughout the available data. This plot is meant, like the one above, to highlight average operational time for picking and preparation phases.

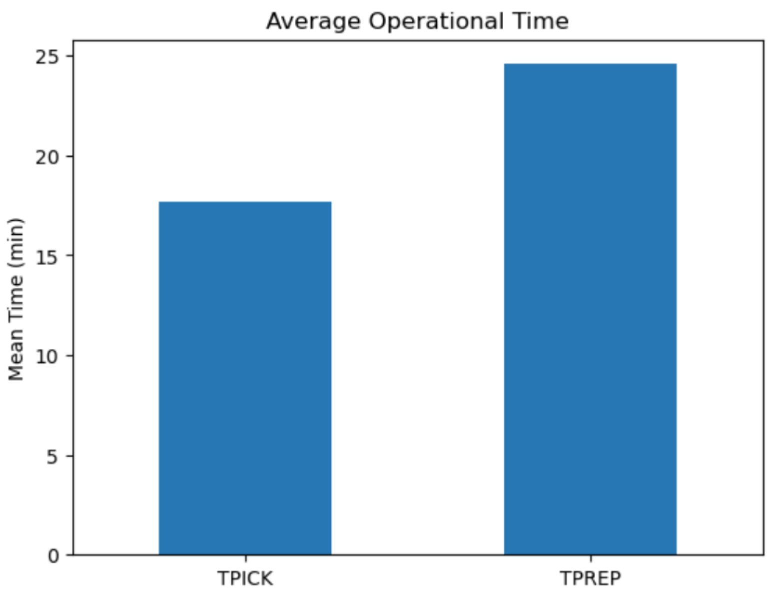

Figure 4.11: A plot visualizing the average operational time for the picking and preparation phases

Figure 4.12, shows the average surgery time for each OR. This could be an interesting trend to monitor over time, which could lead to more insights regarding OR allocation.

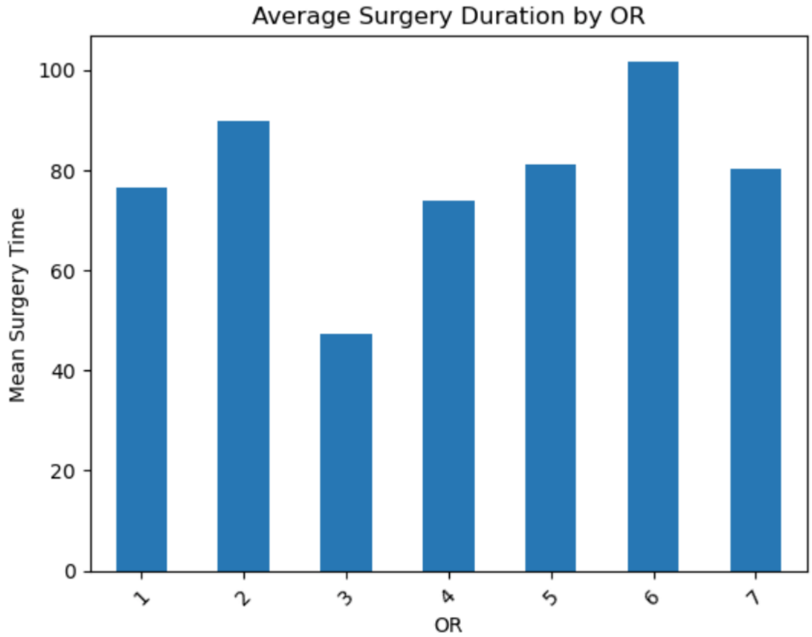

Figure 4.12: A plot illustrating the average surgery duration by OR, in minutes

Figure 4.13 depicts the effective picking time, split over the different surgery groups. This could lead to meaningful insights over time, and further frame the observed complexity of different picking phases.

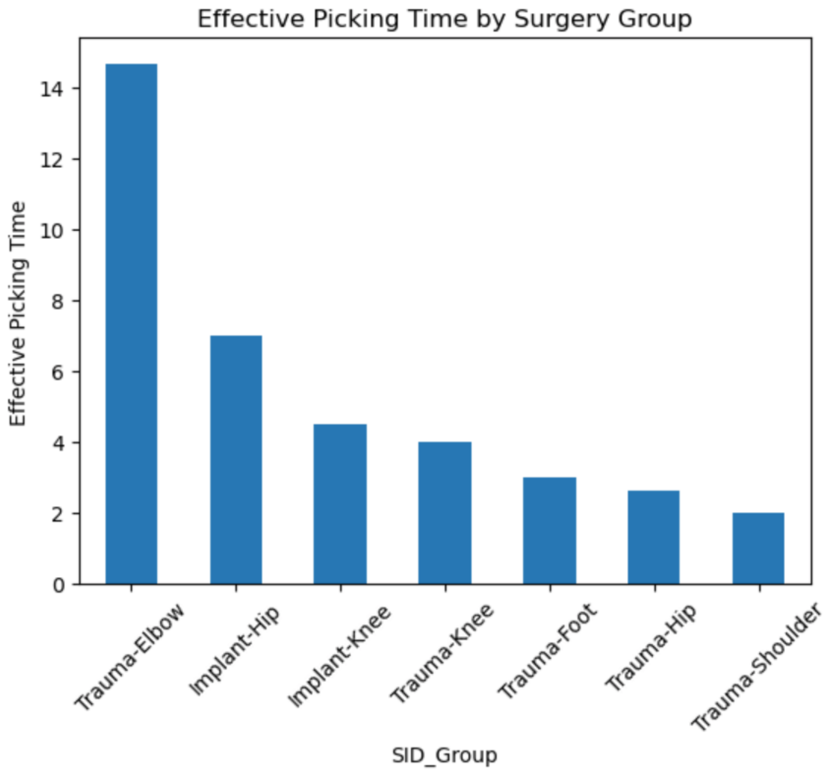

Figure 4.13: A plot illustrating the effective picking time per surgery group, in minutes

In Figure 4.14, the efficiency ratio (dividing the total time spent on the picking process with the effective time picking) is displayed, showcasing how much time an OR nurse spends on effective picking versus the actual time from start to finish.

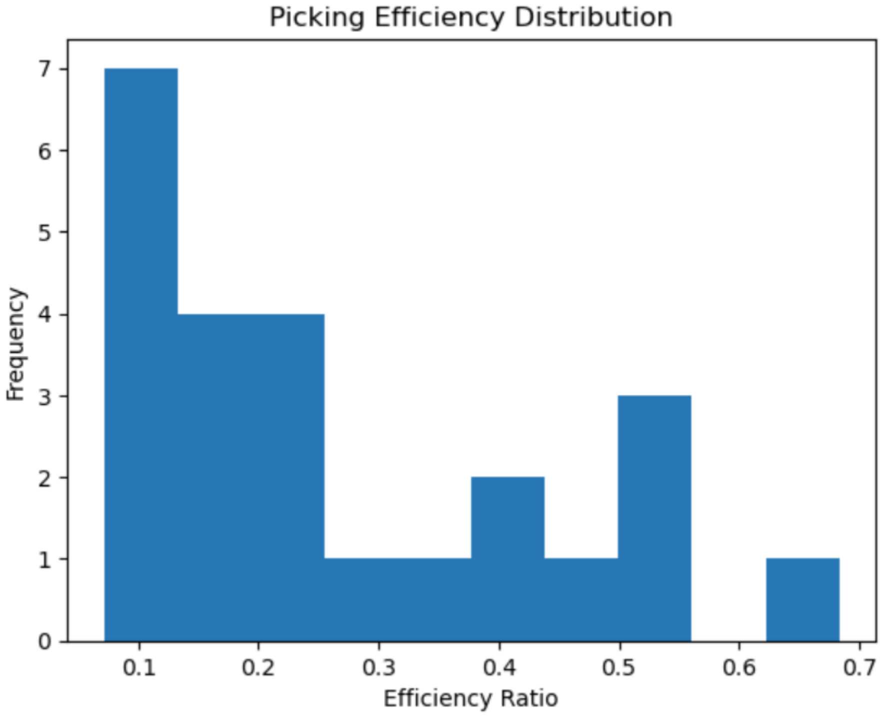

Figure 4.14: Illustration of the frequency of picking efficiency distribution

Figure 4.15 showcases the spread of the average efficient picking time per different surgery-type. The figure illustrates that from the shadowing study, Trauma-Foot-surgeries spend over a third of the time on effective picking, versus Trauma-Shoulder-surgeries spending less than 15 percent of the time on effective picking.

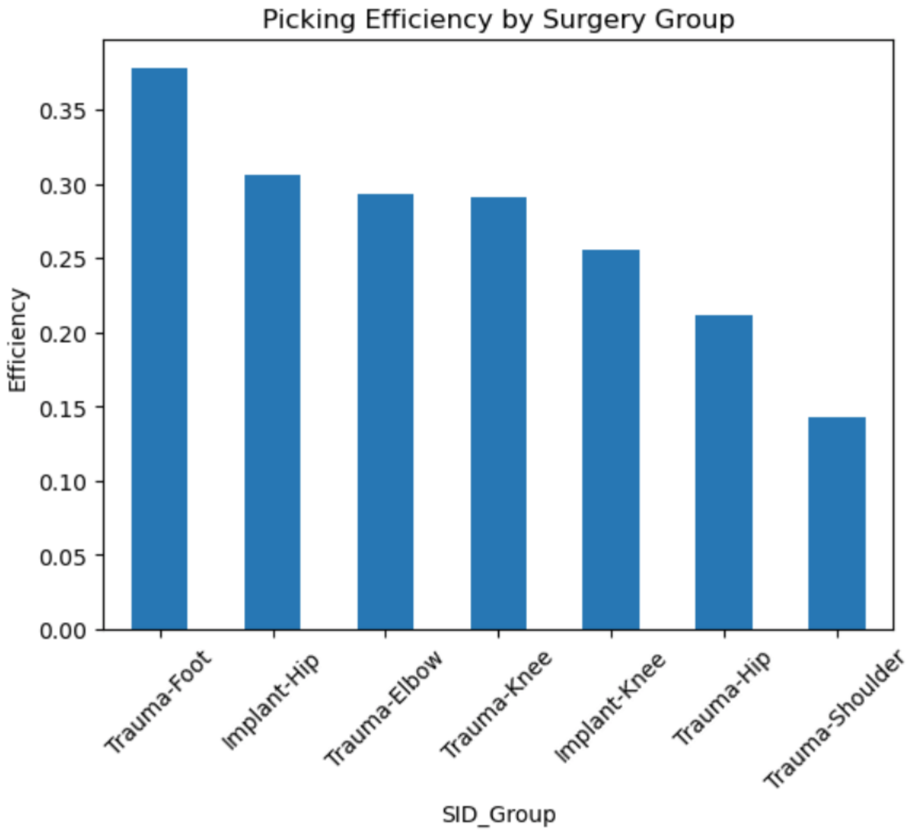

Figure 4.15: Illustration of the average efficient picking time by surgery group

4.2.5 Optimization - Process Mining

Process mining was applied to explore how the observed picking workflows could be represented as process models. Rather than assuming that the workflow follows the intended process sequence, the process models were generated from the available event data. This made it possible to visualize the observed activity patterns and identify where interruptions occurred in relation to the recorded workflow steps.

Figure 4.16 shows the picking workflow visualized using an inductive miner. The model provides an overview of the observed process and illustrates how interruptions occurred within the picking phase. As shown in the figure, the interruptions appear between `SPICK`, representing the start of the picking process, and `STRANS`, representing the start of transportation. Since transportation occurs at the end of the picking process, this indicates that the recorded interruptions took place during picking rather than before or after the process.

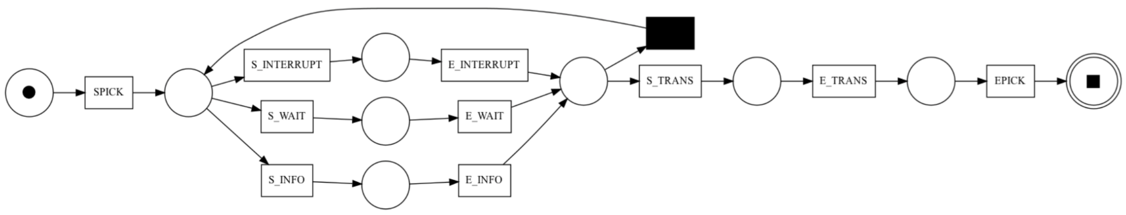

Figure 4.16: An overview of the picking phase generated using an inductive miner with process mining

The inductive miner model also includes an invisible transition, represented by a closed box. This indicates a transition required by the model structure but not directly present as an observed activity in the event data. In this case, the invisible transition appears between recorded workflow steps and reflects that the event log does not include all intermediate actions needed to describe the full sequence in detail.

Figure 4.17 presents the same event data using an alpha miner. Unlike the inductive miner, the alpha miner represents the observed transitions more explicitly and does not simplify the model in the same way. This results in a more nested and detailed process model, closer to the process map depicted in Figure 2.3. The alpha miner visualization therefore shows more of the recorded transition structure, while the inductive miner provides a more simplified overview of the picking phase.

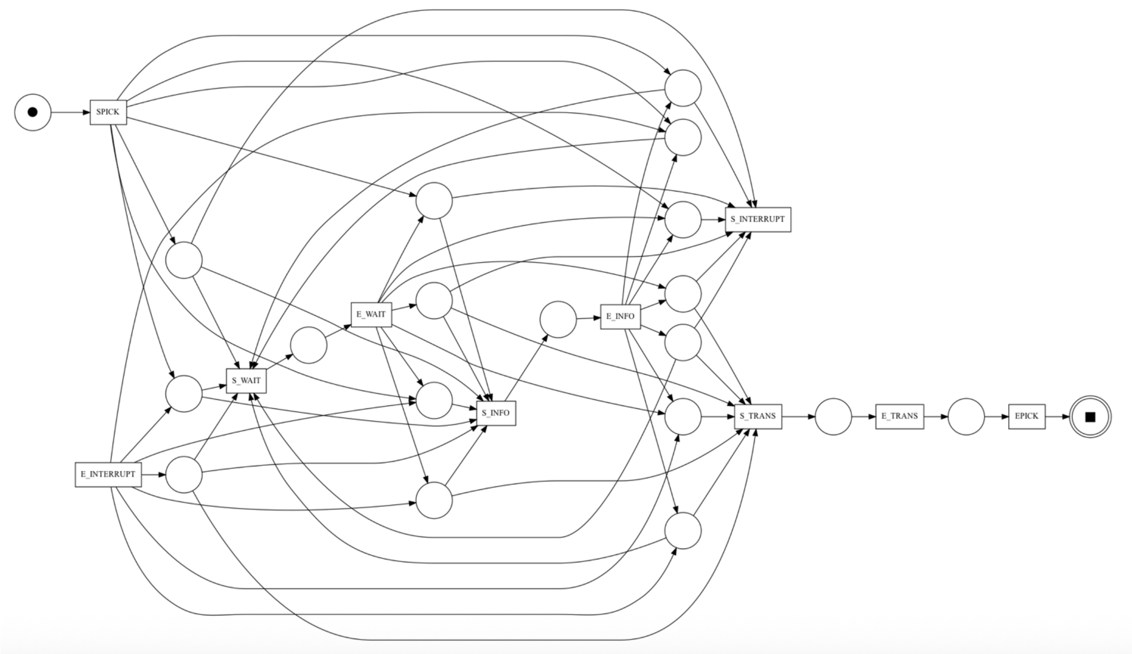

Figure 4.17: A process mining illustration of the picking phase generated using an alpha miner

Figure 4.18 shows the most common path identified in the picking workflow, a so called "Happy path", and indicates where deviations from this path occur. The visualization provides an overview of the activity sequence extracted from the event log and highlights the recurring positions of interruptions within the picking process.

In the dataset from the shadowing study, no observed workflow was completely interruption-free. As a result, the most common path identified in the model includes interruptions. This means that, within this dataset, interruptions form part of the most frequently observed workflow sequence rather than appearing only as deviations from an interruption-free process.

A bigger version of Figure 4.18 is found in Appendix E, as Figure E.1.

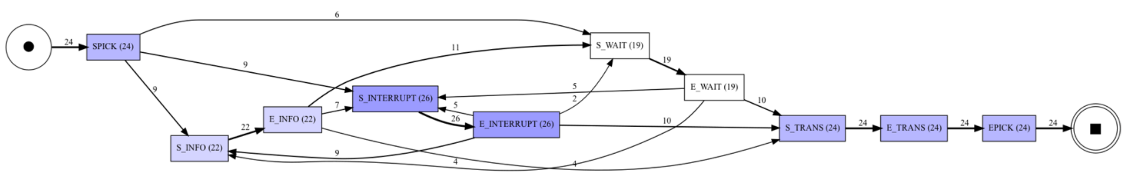

Figure 4.18: Showcasing the "Happy path" and deviating paths in the picking workflow

4.2.6 Data Presentation and Interpretation

The analysis of the dataset highlights several challenges related to the interpretation of workflow data. While the quantitative results provide insights into time consumption, interruptions, and variability across workflows, these findings are not always immediately intuitive or easily interpretable without additional context.

To support interpretation, process models in the form of Petri nets were constructed. These models provide a structured representation of the workflows and allow the observed processes to be visualized based on the collected data. Compared to the conceptual process map presented in Figure 2.3, which offers a simplified example overview of the picking workflow, these models provide a more detailed representation of how individual steps contribute to the overall process.

The variability observed across individual workflows and procedure types makes it difficult to identify clear patterns. In particular, when analyzing data at the level of individual surgical procedures (`SID`), the limited number of observations per procedure restricts the ability to compare them.

By aggregating the data at the level of surgical categories (based on the first two digits of the (`SID`)), a higher number of observations per group is obtained. This enables more robust comparisons between procedure types. From this grouping, it can be observed that certain categories exhibit higher combined mean times for waiting and information search than others, as previously stated.

The results further indicate that different representations of the data reveal different aspects of the workflow. The results also state that the data quality is not good enough to draw any statistical conclusions. Aggregated metrics provide an overview of general patterns, while more detailed representations highlight variability within individual workflows. Similarly, process-based visualizations emphasize how time is distributed across workflow steps and where bottlenecks appear, whereas descriptive statistics and charts make relationships between variables more explicit.

4.2.7 Improvement Metrics

In order to track wether any improvement has been made over time at the hospital, one interesting methodology that can be applied is an alternative application of the Green Cross (GC) methodology. GC methodology is a widely established method which has its original focus on risk management and risk follow-up [48]. However, the purposed alternative application of the GC methodology has its main focus on, instead of risks, wrongly picked items. This information can be readily extracted from the prototype and would in fact lead to no extra work for the personnel. The resulting Figure 4.19, can then be used to track this specific metric over time, and be used as a way of indicating improvement over time. In the image, each square represents one day of the month, where the colors represent the following: Green - there has been no mispicks. Red - there has been a mispick, where the amount of wrongly picked items are represented by the number in the square, and the larger the number is, the darker the shade of red appears.

Mon	Tue	Wed	Thu	Fri	Sat	Sun
		1 No deviations	2 Deviations: 1	3 No deviations	4 Deviations: 1	5 No deviations
6 Deviations: 2	7 No deviations	8 No deviations	9 Deviations: 2	10 No deviations	11 No deviations	12 No deviations
13 No deviations	14 Deviations: 1	15 No deviations	16 No deviations	17 No deviations	18 Deviations: 1	19 No deviations
20 No deviations	21 No deviations	22 Deviations: 1	23 No deviations	24 No deviations	25 No deviations	26 No deviations
27 No deviations	28 Deviations: 3	29 No deviations	30 No deviations			

Figure 4.19: An example of how a Green Cross methodology could be used to track improvements over time

This method is not intended for individual performance monitoring, but as a system-level indicator for tracking changes in mispicked or misplaced items over time, assessing whether implemented workflow improvements are reflected in clinical practice.

5
Discussion

5.1 Discussion of the Results

The following section interprets the findings presented in the Results chapter in light of the study's purpose, the theoretical framework, and the contextual insights obtained through interviews. The discussion moves from specific observations about the picking process and its disruptions toward broader implications for workflow design, staff roles, and data-driven approaches in perioperative environments.

5.1.1 Valuable Insights from Interviews

The interview findings indicate that the picking process is highly dependent on individual knowledge and sensitive to inconsistencies in information availability. These factors are closely linked: fragmented and incomplete formal information systems increase reliance on tacit knowledge accumulated through clinical experience. This creates a workflow that could function under normal conditions, but becomes very fragile under pressure, particularly for less experienced staff.

5.1.2 Underlying Causes of Workflow Disruptions

Across all interviews, information fragmentation emerged as the most consistent source of disruption. Nurses described the need to consult multiple systems, procedure cards, surgeons for their preferences, and physical inventory records, to gather the information required for a single picking process. Accessing these systems, particularly through shared terminals requiring repeated logins, was itself identified as a frequent source of time wasting.

In addition to interruptions, several other forms of disruptions were observed, such as delays caused by frequent task switching between information retrieval, communication, and material handling. Furthermore, coordination delays between roles, particularly when awaiting confirmation from scheduling staff or information from surgeons, contribute to disrupted workflows.

The consequences extend beyond time loss. When no single system provides a complete view, the responsibility for assembling information shifts to the individual nurse. Experienced staff mitigate this through tacit knowledge, while less experienced staff rely on colleagues, generating interruptions that propagate through the workflow. This was directly observed during a facility tour, where an experienced

OR nurse was interrupted four times within a ten minute period to assist colleagues.

The relationship between information fragmentation and interruptions is therefore structural rather than incidental. Fragmented information creates knowledge dependencies, which in turn generate interruptions and concentrate cognitive load on experienced staff. This reduces their availability for tasks that require their expertise and highlights information integration as a prerequisite for improving workflow efficiency and sustainability.

While this tacit knowledge supports operational efficiency, it introduces organizational risk. It is undocumented, difficult to transfer, and not scalable. The department's resilience is therefore partially dependent on specific individuals rather than effective systems. A well-designed digital solution could reduce this dependency by externalizing and standardizing knowledge that is currently implicit.

5.1.3 Staff Role Allocation

The interviews also highlight the relationship between information quality and staffing requirements. Although the picking process is currently performed by OR nurses, this appears to be driven not by task complexity, but by the need to compensate for incomplete or inaccessible information.

If information systems were improved, elements of the picking process could potentially be performed by assistant nurses, allowing OR nurses to focus on tasks requiring clinical expertise, such as patient care and intraoperative support. This could improve resource utilization and reduce cognitive load. However, such changes would require careful consideration of safety, workflow integration, and staff acceptance, and should be viewed as a potential implication rather than a direct recommendation.

5.1.4 Reschedules

In addition to routine interruptions, rescheduling emerged as a major source of disruption with significant operational consequences. Unlike short interruptions, rescheduling events can invalidate completed work, including prepared sterile materials that must be discarded or reprocessed if a surgery is postponed after preparation has begun, shown in the process map of how the different flows interact, in Figure 4.1.

Interview findings suggest that information regarding schedule changes sometimes fail to reach relevant staff in time. This appears less a technological limitation and more a communication and organizational challenge, where responsibility for distributing updates is concentrated in a single role operating under high workload. The result is recurring and avoidable resource waste in terms of time, materials, and preparation effort.

An integrated digital solution could potentially mitigate this issue by automatically distributing scheduling updates to all relevant staff. In addition, systematic logging of rescheduling events would enable pattern analysis over time, supporting more proactive planning and decision-making.

5.1.5 The Updated Process Map

The updated process map presented in Figure 4.1 provides a more complete representation of the perioperative workflow by explicitly integrating material and surgical flows. Unlike simplified linear models, it highlights how disruptions, particularly rescheduling events, propagate across both dimensions. This representation emphasizes that these are not separate processes, but interconnected aspects of a single workflow. A disruption in one dimension directly affects the other.

A critical point occurs when rescheduling takes place after preparation has begun. At this stage, sterile materials that have already been opened become unusable and must enter a transitional state before reprocessing. Single-use items are deemed consumed, and are thrown away. This transit phase represents a period of uncertainty, during which materials are neither available nor fully reintegrated into the system, complicating inventory management and planning.

By explicitly representing these transitions, the process map provides a more realistic view of how disruptions impact workflow continuity and resource availability. It also serves as a conceptual foundation for identifying which events and states could be captured in a digital system to support material tracking and analysis of rescheduling patterns.

5.1.6 Data Visualization for Relevant Stakeholders

The findings of this thesis indicate that the practical value of workflow data depends not only on the analytical methods applied, but also on how the resulting insights are structured and communicated. In perioperative workflows, relevant stakeholders differ in their responsibilities, time constraints, and familiarity with analytical tools. As a result, the same underlying data may require different forms of presentation.

The perioperative workflow contains temporal variation, interruptions, information searches, waiting periods, material dependencies, and deviations from expected activity sequences. These dimensions are difficult to communicate through one isolated metric or visualization. Instead, the findings suggest that workflow data should be presented through a combination of aggregated summaries, time-based visualizations, and process-oriented representations. Each type of visualization highlights a different aspect of the workflow and supports a different form of interpretation, for perhaps a different stakeholder.

For OR nurses and other clinical staff, visualizations should primarily support reflection and shared understanding rather than individual performance monitoring. Since clinical staff operate in time-constrained environments, visual outputs need to be simple, recognizable, and directly connected to practical workflow problems. For example, visualizations showing which procedure types are associated with high information search time, waiting time, or frequent interruptions could support discussions about procedure cards, material lists, and communication routines. However, such visualizations must be framed carefully. If they are perceived as tools for evaluating individual nurses, they may reduce trust and create resistance. The focus should therefore be on identifying system-level causes of inefficiency rather than attributing delays or disruptions to specific individuals.

For staff responsible for procedure cards and preparation routines, more detailed visualizations may be valuable. Comparisons between procedure types, picking duration, information search time, and additional or incorrectly picked items could help identify where formal documentation does not correspond to practical workflow needs. This is particularly relevant given the interview findings showing that experienced nurses often compensate for incomplete or outdated information through tacit knowledge. In this context, visualization can support a transition from experience-dependent routines toward more systematically maintained information structures.

For schedulers and administrative personnel, the relevant level of detail is different. These stakeholders are less concerned with each individual picking process and more concerned with patterns across procedures, time periods, and resource demands. Aggregated visualizations showing preparation time, rescheduling frequency, workload variation, and recurring bottlenecks could support planning and resource allocation. Weekly or monthly summaries may therefore be more useful than real-time dashboards, as the purpose is not immediate clinical action but retrospective evaluation and prospective planning.

The dashboard examples in Section 4.2.4 illustrate how perioperative workflow data can be translated into stakeholder-facing KPIs. Broader operational indicators, such as number of surgeries, average picking and preparation times, and surgery duration per OR, may support administrative personnel, schedulers, and of course hospital management by providing an overview of workload, capacity, and time distribution. These indicators value lies in supporting stakeholder-adapted visualization, shared understanding, identification of bottlenecks, and follow-up of workflow improvements over time.

For inventory and sterile central personnel, visualization should focus on material availability, material states, and the consequences of rescheduling. The updated process map developed in this thesis, Figure 4.1, illustrates that materials may move through several states, including picked, prepared, contaminated, in transit, and returned for sterilization. If these states were captured digitally, visual representations could provide a clearer overview of which materials are available, temporarily unavailable, or in need of prioritization for reprocessing. This could be particularly valuable when materials are shared across multiple procedures or risk being double-booked.

For hospital management, visualization should support strategic interpretation rather than operational detail. Management-level visualizations should therefore focus on trends, bottlenecks, resource waste, and improvement opportunities. Aggregated process maps, time-distribution charts, and summaries of rescheduling-related material waste could help identify where workflow redesign, staffing changes, or digital integration may be justified. In this sense, visualization can support decision-making by translating local workflow observations into organizational-level insight.

Management could also benefit from monthly update regarding improvement metrics, this could for example be a visualization mimicking the GC methodology, mentioned in Section 4.2.7.

For Mölnlycke, visualizations may serve an additional role by informing the further development of digital solutions. Visual outputs can help identify which data points are most relevant to collect, which workflow states should be represented in the system, and where digital support could reduce information gaps. However, this role should be understood as secondary to the clinical and organizational purpose of the data. The primary aim of visualization in this context should be to support healthcare stakeholders in understanding and improving their workflows, rather than merely demonstrating the capabilities of a digital product. It could also be collected, analyzed, and presented internally to understand the difference this digital solution is making, and what should be the focus of implementation when the next hospital is looking to digitalize their perioperative flow.

A key implication is that data visualization should not be treated as a neutral technical output. The same data can support different interpretations depending on how it is aggregated, contextualized, and presented. A detailed process mining model may be valuable for analysts or system developers, but maybe too complex for clinical staff. In contrast, a simplified dashboard may support a quick overview but fail to explain the underlying causes of inefficiency. Effective visualization therefore requires alignment between the analytical representation and the decision context in which it will be used.

This also highlights the importance of data storytelling. The visualizations produced in this thesis, including time-distribution plots, correlation matrices, and process maps, are most meaningful when interpreted together with qualitative insights from interviews. For example, a correlation between nurse experience and time spent searching for information becomes more informative when connected to the interview finding that experienced nurses rely on tacit knowledge to compensate for fragmented information systems. Without such context, visualizations risk remaining descriptive rather than explanatory.

Overall, the findings suggest that stakeholder-adapted visualization is necessary for making workflow data practically meaningful. This does not mean that each stakeholder requires entirely separate datasets, but rather that the same underlying data should be filtered, aggregated, and contextualized differently depending on its intended use. When designed in this way, visualization can support shared understanding across clinical, administrative, and industrial stakeholders, helping translate fragmented workflow data into actionable knowledge. Its ultimate goal is therefore not only to communicate results, but to improve stakeholder understanding and provide a foundation for data-driven decision support.

5.1.7 Significance of the Thesis

The State of the Art identifies four main gaps that this thesis addresses: the under-explored research on the material picking process, the lack of attention to OR nurses' cognitive load, the role of information fragmentation in perioperative workflow, and the limitation of existing process mining applications within the surgical workflow. This thesis does not resolve these gaps fully, but it contributes to addressing them by providing an exploratory, empirically grounded analysis of a workflow area that remains largely unexplored in existing data-driven OR research.

Previous research on OR efficiency has primarily focused on surgical scheduling, resource utilization, patient flow, and procedure duration, while the material picking process performed by OR nurses has received limited academic attention. By studying the process directly through observational shadowing and semi-structured interviews, this thesis provides insight into why this part of the workflow is difficult to analyze using conventional data-driven methods. The findings indicate that the picking process generates few structured digital traces in current hospital systems. It is performed through a combination of informal knowledge, analogue documentation such as procedure cards and inventory binders, and verbal communication between staff. As a result, the process is largely invisible to data extraction methods that rely on structured event logs from hospital information systems. Existing data-driven approaches are therefore limited in their ability to capture this part of the workflow without complementary observational and qualitative data.

The thesis also contributes to the understanding of cognitive load and knowledge dependencies in the preoperative workflow. The findings indicate that cognitive load is not only related to the number of tasks performed, but also to the uncertainty created by incomplete or fragmented information. When procedure cards, surgeon preferences, material availability, and scheduling information are distributed across multiple sources, the responsibility for assembling a complete understanding of the task shifts to the individual nurse. This creates dependencies between staff members and contributes to interruptions during the picking process. In this way, information fragmentation drives knowledge dependency, interruptions, and cognitive burden.

Furthermore, the findings suggest that information fragmentation should be understood as a structural workflow problem rather than merely a background condition. Fragmented information can contribute to repeated communication, additional searches, waiting time, incorrect or unnecessary picking, and increased dependence on experienced staff. The updated process map presented in this thesis further illustrates how disruptions such as rescheduling can propagate across both surgical and material flows. This provides a visual and conceptual basis for understanding information fragmentation as a systemic problem. From this perspective, improvement efforts should not only optimize individual workflow steps, but also address how information is connected across roles and phases of the perioperative workflow.

Additionally, the thesis contributes methodologically by exploring the potential and limitations of process mining in a perioperative context. While existing healthcare applications often rely on structured event data and focus on costs or patient flows, this thesis applies process mining to the picking process from the perspective of healthcare personnel, where several activities are not routinely captured in hospital information systems.

The differentiation from current research therefore lies in the thesis' focus on an underrepresented workflow, its explanation of how information fragmentation contributes to cognitive load and interruptions, and its exploratory application of process-oriented analysis to incomplete workflow data. Rather than presenting definitive or statistically generalizable conclusions, the thesis provides a foundation for further research, improved data collection, and future development of stakeholder-adapted decision support in perioperative material workflows.

5.2 Discussion of the Methodology

The methodological approach adopted in this thesis was shaped by practical constraints in a clinical environment, limited availability of structured workflow data, and the exploratory nature of the study. This section reflects on key methodological choices to contextualize the findings and ensure transparency regarding the limitations of the adopted approach.

5.2.1 Exploratory Research Design

The choice of an exploratory research design was motivated by the current state of knowledge in the field. As established in the State of the art, Section 1.2, the material picking process in perioperative workflows remains under-researched. While OR efficiency and surgical scheduling are well studied, the operational and cognitive challenges associated with material preparation performed by OR nurses have received limited attention. Exploratory designs are appropriate when the aim is to describe and map a phenomenon prior to explanation or prediction, which aligns with the purpose of this thesis.

The exploratory approach also enabled responsiveness to emerging findings, particularly during interviews, where issues such as double-booked materials and rescheduling overflows were identified. A more rigid design would likely have overlooked these insights, indicating that methodological flexibility contributed to the depth and practical relevance of the results.

5.2.2 Trade-offs Between Realism and Statistical Robustness

The methodological choices reflect a trade-off between realism and statistical robustness. Observational data collected in a clinical setting provides high ecological validity, as the findings reflect actual workflow behavior rather than controlled or simulated conditions. This is important in complex environments such as perioperative workflows, where relevant variables are difficult to isolate experimentally.

However, this realism comes at the cost of statistical power and data consistency. The limited number of observations, variability between workflows, and presence of subjective measurements restrict the use of advanced statistical methods and prevent statistically generalizable conclusions. Rather than treating this as a failure of the study design, the thesis adopts an exploratory perspective, focusing on identifying meaningful variables, relationships, and requirements for future data collection. The emphasis therefore shifts from producing definitive conclusions to understanding the conditions necessary for reliable and actionable analysis.

5.2.3 Observer Influence and Subjectivity

The use of shadowing as a data collection method introduces the possibility of observer influence on participant behavior, commonly referred to as the Hawthorne effect. The presence of observers may have affected how healthcare personnel performed tasks or responded during the observation period. While this limitation cannot be fully eliminated, the consistency of observed disruptions indicates that the findings are unlikely to be solely attributable to observer influence.

Additionally, certain variables, such as perceived complexity, rely on subjective assessments made during observation. Nevertheless, some degree of subjectivity remains unavoidable and is reflected in the cautious interpretation of the findings.

5.2.4 Use of Synthetic Data and Imputation

Where gaps remained in the dataset following the interview phase, iterative imputation was used to generate synthetic values. This approach was applied cautiously and only when necessary to maintain dataset completeness for exploratory analysis. The imputed values were informed by available data and contextual input from healthcare professionals, but they still introduce assumptions that are not present in directly observed variables.

The decision to impute rather than exclude incomplete observations reflects a trade-off between dataset completeness and analytical reliability. Removing incomplete cases would have further reduced an already limited dataset, while imputation allowed for exploratory pattern identification. As the primary purpose of the dataset was to illustrate how structured workflow data can be analyzed and visualized, no conclusions are based solely on imputed variables, and all such findings are treated as indicative rather than definitive.

5.2.5 Applied Process Mining for Actionable Insights

Process mining, has shown to be a very powerful tool for generating an overview for the workflows. What makes process mining so good in this particular instance is that it is easy to understand, gives direct actionable insights, and it is easy to collect event data in the form of an activity log. Process mining would combine all the separate flows and visualize it in a way that is easily interpretable and can be angled towards different stakeholders.

When process mining has been applied, it can be combined with other data-driven techniques in order to fully utilize its potential. Since multiple stakeholders are interested in the data generated through the workflows, visualizations and extractions will have to be made with this in mind.

By integrating machine learning with the data generated through process mining, it is possible to develop prediction-based decision support. For a future prototype solution, machine learning could be used within the solution to predict whether a surgery is likely to be rescheduled. However, the extent to which such predictions would provide meaningful insights is uncertain, as rescheduling is influenced by several underlying factors that may not be fully captured in the available data. Beyond this, the prototype could also be used to predict time-related constraints associated with different events in the surgical workflow. Such insights could support more informed scheduling decisions and contribute to improved planning of surgical activities.

A future prototype could, if integrated fully with the existing information systems, predict material stock levels. These prognoses can then be the underlying support for when purchases should be made and further strengthen the material availability.

5.2.6 Methodological Contribution

Beyond its empirical findings, this study contributes methodologically by demonstrating how partial and heterogeneous data can be structured and analyzed in a complex healthcare context. It illustrates how qualitative insights can be systematically integrated with quantitative observations to address limitations in data completeness and quality. The study also highlights how exploratory analysis can be used to identify meaningful variables and define requirements for future data collection in digital healthcare systems. Overall, the approach shows that useful insights can be derived from incomplete data when supported by contextual understanding, and emphasizes the importance of aligning data collection with analytical objectives in future implementations.

5.3 Limitations

This section first discusses limitations related to the dataset and data collection, followed by limitations connected to interpretation, stakeholder representation, process mining, implementation risks, and transferability.

5.3.1 Significance of Dataset

The dataset analyzed in this study is limited in both size and statistical robustness, exhibiting multicollinearity and the presence of extreme outliers. The shadowing study documented 24 workflows over the course of five days, and when combined with observer influence and the subjectivity involved in assessing surgical complexity, the dataset does not support statistically generalizable conclusions. The findings should therefore be interpreted as indicative rather than definitive, and understood within the exploratory scope of the study.

Despite these limitations, the dataset retains analytical value. Its strength lies not in statistical power but in its ability to illustrate what structured workflow data can reveal when collected systematically. The visualizations and correlation patterns presented in the Results chapter demonstrate that even a limited dataset can surface meaningful patterns related to time distribution, interruption frequency, and variability. These patterns are currently not visible to hospital stakeholders due to the absence of structured data collection in this part of the workflow.

It is also important to note that the primary variable of interest in the shadowing study, interruptions, is not directly transferable to a system-based data collection approach. Requiring healthcare personnel to manually report each interruption would likely lead to underreporting and reduced usability of the system. A more feasible approach is to infer disruptions indirectly through activity logs and timestamp patterns, where deviations from expected workflows can serve as representatives for interruptions and inefficiencies.

5.3.2 Observational Data Versus System-Generated Data

A key distinction must be made between the data collected through shadowing and interviews, and the data that can be captured through a digital solution in routine clinical use. The dataset used in this thesis originates from a shadowing study focused on interruptions in the preoperative workflow and was not initially intended for structured analytical use. This is reflected in its incompleteness and variability. As such, the dataset should be understood as a proof of concept rather than a fully developed analytical resource.

Observational methods enable the identification of workflow characteristics that are difficult to capture through digital systems alone. These include the frequency of interruptions, the cognitive effort associated with information retrieval, and informal communication patterns between staff. Such factors are central to understanding workflow inefficiencies but are not readily observable in system-generated data.

In contrast, system-generated data offers advantages in scale, consistency, and longitudinal coverage. A digital solution deployed in a clinical setting could capture comprehensive event logs, including timestamps and material flows, across all workflows. This would enable more robust statistical analysis, and process mining at a level of detail that observational data from shadowing studies have trouble supporting.

The implication is that these data types are complementary rather than interchangeable. Observational data provides insight into what should be measured and why, while system-generated data enables large-scale and consistent measurement. The shadowing dataset should therefore be understood as informing future data collection and system design, rather than as a standalone basis for analysis.

5.3.3 Role of Qualitative Insights

The quantitative data collected through the shadowing study is limited in size, and several observed patterns are difficult to interpret without additional context. The qualitative findings from semi-structured interviews provide this context, enabling a more meaningful interpretation of the quantitative results.

For example, the observed negative correlation between nurse experience and time spent searching for information becomes more informative when interpreted alongside interview findings. These indicate that experienced nurses rely on tacit knowledge accumulated through practice to compensate for fragmented information systems. The quantitative pattern alone identifies the relationship, while the qualitative data explains the underlying mechanism.

At the same time, qualitative data introduces limitations. Interview responses are inherently subjective and may not generalize beyond the specific context in which they were collected. However, when combined with quantitative observations, they provide a more balanced and robust understanding of the workflow.

Without contextual understanding, numerical patterns risk misinterpretation. Together, the two approaches serve complementary roles: quantitative analysis identifies patterns and relationships, while qualitative insights provide the contextual understanding necessary to interpret them. This combination strengthens the overall validity of the findings within the exploratory scope of the study.

5.3.4 Limited Stakeholder Input

The number of interviews was also limited. While the interviewed OR nurses provided rich and relevant contextual insights, additional interviews with a broader range of stakeholders would have strengthened the study. In particular, perspectives from assistant nurses, schedulers, sterile central personnel, surgeons, and hospital management could have provided a more complete understanding of how disruptions propagate across the perioperative workflow. Interviews at additional hospitals would also have enabled comparison across different organizational contexts and provided a broader view of how material preparation workflows vary between sites.

It should also be noted that the interview findings were broadly consistent with contextual insights from previous interviews and field observations conducted by Mölnlycke at other Swedish hospitals [4]. These insights were not treated as formal empirical data in this thesis, but they suggest that several of the identified challenges occur beyond the observed department.

Together, these limitations mean that the qualitative findings should be interpreted as informed perspectives from a specific clinical context rather than comprehensive representations of all stakeholder groups or hospital settings. However, the consistency between the findings of this thesis and prior contextual insights from Mölnlycke suggests that the identified problems may reflect broader challenges in perioperative material workflows. This does not make the findings statistically generalizable, but it strengthens their practical relevance.

5.3.5 Limitations of Process Mining

Moving forward with the application of process mining, it must be said that it has its limitations. Process mining in itself only visualizes the event logs that gets fed into it. This means that process mining as a technique is only as good as the data that it processes. This puts a substantial burden on the data collection and data quality, where one bad flow effectively could distort the whole flow representation or lead to misleading conclusions.

5.3.6 Implementation and Data Quality Risks

Introducing a digital solution into an established clinical workflow involves several practical, technical, and ethical risks. While the findings of this thesis suggest that integrated information systems and structured workflow data could support improved coordination and decision-making, such benefits depend on how the solution is implemented, adopted, and administrated in practice. Since there is no way to know beforehand to what level a prototype will be integrated with the current systems, recommendations are to be seen as purely theoretical.

A central risk concerns user adoption. OR nurses already operate under high cognitive load and time pressure, meaning that any new digital tool must clearly reduce workload rather than adding additional steps. If the system is perceived as a burden, requiring duplicate documentation or interrupting existing routines, staff may develop workarounds or use it inconsistently. This would reduce both the practical value of the solution and the quality of the data collected through it. This risk is particularly relevant given that experienced nurses currently rely on tacit knowledge to manage information gaps. A digital solution must therefore provide information that is sufficiently accurate, accessible, and useful for staff to trust it as part of their daily workflow.

Another important limitation concerns data quality and completeness. The proposed use cases, including process mining, pattern analysis, rescheduling support, and inventory-related decision support, all depend on consistently recorded and high-quality data. The findings of this thesis demonstrate how quickly analytical value is reduced when data is incomplete, inconsistent, or not collected for analytical purposes. If a digital system is used irregularly, or if certain workflow steps are not logged, the resulting dataset may reproduce the same limitations that constrained this study. In such cases, hospitals may expect actionable insights from the system, while the underlying data remains too incomplete to support reliable analysis.

There is also a risk that analytical insights are not communicated in an appropriate way. If data outputs are presented without sufficient context, or if stakeholders receive information that is poorly adapted to their responsibilities, the solution may contribute to further information fragmentation rather than reducing it. For this reason, data presentation must be aligned with stakeholder needs.

Ethical considerations are particularly important because workflow data may be collected at an individual level. Data on who performed a task, how long it took, or how often interruptions occurred can be valuable for identifying system-level inefficiencies, but it also creates a risk of individual performance monitoring. If staff perceive the system as a surveillance tool, trust and adoption are likely to decrease. More importantly, blame-oriented use of the data could shift attention away from structural causes of inefficiency, such as information gaps, material availability problems, unclear responsibilities, and poor coordination. Clear administrative principles are therefore needed to define who can access the data, how it may be used, and how individual staff members are protected.

There is a risk of over-reliance on data-driven decision support. A digital prototype may provide predictive outputs such as estimated picking times, rescheduling risks, or inventory shortage warnings. These outputs can support decision-making, but they should not replace clinical judgment or contextual knowledge. Predictive models are only as reliable as the data on which they are based, and not all relevant aspects of a clinical workflow can be captured digitally. The proposed solution should therefore be understood as a tool for supporting interpretation and decision-making, rather than as a complete or objective representation of clinical reality.

Overall, the proposed solutions should be implemented with caution and with close involvement from clinical stakeholders. Their success depends not only on technical functionality, but also on trust, usability, data quality, system integration, and administration. A digital solution that fails to account for these factors risks becoming an additional source of workload or fragmentation, whereas a carefully implemented solution may support more reliable information flows and more meaningful data-driven improvement.

5.3.7 Generalizability and Transferability

The transferability of the findings is strongest in contexts that resemble the studied setting. This includes Swedish hospital environments with similar perioperative roles, material preparation routines, documentation practices, and fragmented information systems. Since the study focuses on elective procedures, the findings are more applicable to planned surgical workflows than to trauma or emergency surgery. Trauma workflows operate under more unpredictable conditions, where preparation may need to occur under severe time pressure and with incomplete information. The hectic and unpredictable nature of trauma workflows may also make systematic data collection more difficult. Any transfer of the findings to emergency surgical contexts would therefore require significant adaptation.

Although the empirical findings are context-dependent, the methodological approach is more transferable. The combination of observational workflow data, semi-structured interviews, process-oriented analysis, and stakeholder-adapted visualization provides a replicable approach for studying material-related perioperative workflows in other hospital settings. This may be particularly relevant for future implementations of digital systems, where locally collected event data could be analyzed to generate institution-specific insights rather than assuming that findings from one hospital apply directly to another.

At the same time, no hospital workflow is identical. Differences may exist not only between hospitals, but also between departments within the same hospital. These differences may concern staff roles, local routines, procedure types, information systems, material management systems, and the degree of digital integration. As a result, data collected in one hospital cannot be assumed to be directly applicable to another hospital or department.

This means that the proposed approach should not be understood as a one-size-fits-all solution. By instead tailoring the methodological approach to local workflows, systems, and stakeholder needs, the insights generated are more likely to be relevant, interpretable, and actionable.

Overall, the numerical findings of this thesis should be interpreted as context-specific, while the identified mechanisms and methodological approach are potentially transferable. The findings should therefore be viewed as an analytical foundation for local adaptation rather than as conclusions that can be directly applied across all hospital settings.

5.3.8 What We Could Have Done Differently

If the study were to be repeated, one important improvement would be to secure access to a more complete and structured dataset at an earlier stage. Initially, synthetic data was considered as a way to complement missing empirical data and enable broader analyses. However, after more research regarding synthetic data, it became obvious that the time-frame of this thesis would not be sufficient. The study instead relied primarily on the available observational data.

A second improvement would be to conduct a new, longer and more in-depth shadowing study. This would allow more workflows to be observed across more days, procedures, and staffing conditions, providing a stronger basis for identifying recurring patterns and disruptions. A new shadowing study would also allow for other parameters to be collected, since the original shadowing study's focus was to mainly measure the number of interruptions.

Finally, the interviews could have included a broader range of healthcare personnel. While OR nurses were highly relevant due to their central role in the picking and preparation processes, perspectives from other stakeholders could have provided a more complete understanding of how disruptions arise and propagate across the perioperative workflow. Although it was not possible, it would have strengthened the findings and discussion.

5.4 Future Work

The findings of this thesis indicate several considerations for future implementation of digital support in perioperative material workflows. These recommendations should not be interpreted as validated solutions, but as design and implementation priorities derived from the empirical findings, methodological limitations, and analytical results of the study. In particular, the results emphasize the importance of structured data collection, integration between information sources, stakeholder-adapted presentation, and careful alignment with clinical work practices.

5.4.1 Collection of more Complete Workflow Data

A first recommendation is that future digital implementations should treat data collection as a core design requirement rather than as a secondary outcome of system use. One of the main limitations of the dataset analyzed in this thesis was that the shadowing data had not originally been collected for analytical purposes. Several variables were incomplete, timestamps were limited, and important workflow events, such as rescheduling and material state changes, were not recorded as structured data points. If future system-generated data is to support meaningful analysis, workflow events should therefore be logged consistently, with clear definitions of activities, timestamps, case identifiers, responsible roles, and relevant contextual information.

At the same time, data collection should be designed to minimize additional workload for clinical staff. The digital solution should capture relevant workflow activities as naturally as possible within existing routines, rather than requiring OR nurses to perform additional documentation tasks during time-critical work. Data should ideally be generated as a by-product of ordinary system use. This is important both for user adoption and for data quality, as a system perceived as burdensome is less likely to be used consistently.

However, data collection alone is not sufficient to solve workflow problems. Data can reveal where time is spent, where interruptions occur, and where deviations from expected workflows appear, but it does not automatically explain why these patterns occur. Future implementations should therefore combine quantitative workflow data with follow-up investigations, staff input, and local process knowledge. In this sense, data should be understood as a foundation for analysis and improvement rather than as a solution in itself.

5.4.2 Integration of Information Systems

The findings indicate that future digital implementations should strengthen the connection between scheduling information, material preparation, and inventory management, by combining multiple information systems. Several disruptions identified in the interviews were related to missing, misplaced, unavailable, or potentially double-booked materials. These issues suggest that the picking process cannot be improved in isolation, but needs to be connected to a broader information flow that includes material availability, sterile supply processes, and planned surgical demand.

Material availability should therefore be represented more explicitly in future systems. A digital solution could support this by assigning operational states to materials, such as available, reserved, picked, prepared, in use, contaminated, in sterilization, or unavailable. This would make it easier for OR personnel to locate materials, understand their current status, and avoid unnecessary interruptions related to item availability or location. It would also allow recurring patterns in missing or incorrectly picked items to be identified over time, providing a basis for targeted improvements in material organization, procedure cards, and inventory routines.

The integration between scheduling and inventory information is particularly important for preventing double-booking and late discovery of material conflicts. If materials required for a scheduled procedure are reserved when the procedure is planned, the system could provide earlier visibility of potential shortages or competing demands. This would not eliminate all material-related disruptions, but it could reduce disruptions caused by limited shared visibility across departments. In cases where material conflicts still occur, structured data on the reason, timing, and consequence of the conflict could support more informed prioritization and follow-up.

The interviews also indicate that sterile central may operate with limited visibility into upcoming surgical demand, while prioritization is often communicated manually, for example by phone. Connecting sterile central to the same information flow could provide earlier insight into which materials will be needed, when they are needed, and which items should be prioritized for sterilization. This could support more proactive planning and reduce delays caused by materials being unavailable or still in sterilization.

Rescheduling should also be integrated into this information flow. The findings show that cancellations and schedule changes can affect both surgical planning and material preparation, especially when materials have already been picked, opened, or contaminated, displayed in Figure 4.1. Future systems should therefore treat rescheduling as a structured workflow event, capturing when the change occurred, where in the workflow it occurred, why it occurred, and which state material reached at the time of the rescheduling. Such data would make it possible to better understand the operational consequences of rescheduling, including unnecessary picking, repeated preparation, material waste, and increased workload.

Overall, integration between scheduling, inventory, sterile central, and material preparation would support a more complete view of the perioperative material workflow. However, such integration depends on reliable data entry, clear responsibility for maintaining material information, and compatibility with existing hospital systems. The goal should not be to assume that all material-related disruptions can be eliminated, but to reduce avoidable disruptions caused by fragmented information, late communication, and lack of shared visibility.

5.4.3 Evaluation of Stakeholder-Adapted Visualizations

Future implementations should avoid presenting the same analytical output to all stakeholders. As discussed in Section 5.1.6, different actors require different levels of detail depending on their responsibilities, decision contexts, and familiarity with analytical tools. Administrative personnel and scheduling staff may benefit from daily or monthly summaries showing where bottlenecks occur and how they vary over time. OR nurses stated in their interviews that they believe it would be beneficial to get detailed workflow feedback, particularly regarding interruptions, information search time, and recurring delays in the picking process.

The interview findings also indicate that staff responsible for procedure cards have a specific interest in summarized reports showing which procedures are associated with long picking times and which parts of the process contribute most to delays. Such information could support more systematic updates of procedure cards and help identify where formal documentation does not correspond to practical workflow needs.

The presentation of data should follow the principles of data storytelling. Visualizations should be interpretable, transparent, and focused on actionable insights rather than exhaustive data display. This is particularly important in healthcare contexts where stakeholders may have different levels of technical familiarity and limited time to interpret analytical outputs. The purpose of reporting should be to support shared understanding and decision-making, not to monitor or single out individuals in the workflow.

5.4.4 Further Development of Process Mining and Decision Support

With more complete and consistently recorded data, the analytical methods explored in this thesis could be applied more robustly. The process mining outputs produced in this study were useful as exploratory visualizations, but the limited number of workflows prevented stronger conclusions. In a future implementation with hundreds or even thousands of logged cases, process mining could be used to identify recurring deviations, bottlenecks, and common workflow variants with greater reliability. This would allow hospitals to move from informal knowledge of workflow problems toward more systematic analysis of where disruptions occur and under what conditions.

In the long term, improved data infrastructure could support more advanced decision support. Potential applications include estimating picking complexity, identifying procedures with elevated risk of rescheduling-related disruption, and forecasting material demand. However, these capabilities should be understood as long-term possibilities rather than immediate outcomes. Predictive models require large volumes of high-quality data, careful validation, and continuous monitoring as workflows change [49]. They should be designed to support clinical and operational judgment, not replace it.

5.4.5 Reducing Dependence on Tacit Knowledge

One of the central findings of this thesis is that the picking process depends heavily on experience and tacit knowledge. Fragmented information sources lead to uncertainty, interruptions, and reliance on experienced OR nurses as informal knowledge holders. A future digital solution should therefore aim to make relevant knowledge more accessible and structured, reducing the need for less experienced staff to interrupt colleagues during the picking process.

This could be achieved through improved procedure cards, searchable material information, live-updated changes from surgeons, clearer item locations, standardized terminology, and structured guidance within the digital solution. More advanced support, such as an internal question-and-answer function or an integrated AI-chatbot, could also be explored in the future. Such assistance could generate valuable secondary insights. For example, recurring questions submitted through the system could indicate where information is unclear, incomplete, or difficult to locate. However, such functionality should be approached cautiously. It would need to be validated carefully, restricted to appropriate information sources, and designed without reliance on sensitive patient data. The purpose should not be to replace clinical expertise, but to make existing organizational knowledge easier to access at the point of need.

The findings also suggest that improved information access may create opportunities to reconsider staff role allocation in the long term. If material requirements become clearer and less dependent on tacit knowledge, some picking-related tasks might potentially be performed by assistant nurses or dedicated logistics staff, allowing OR nurses to focus on surgeries and patient care.

6 Conclusion

The findings in this thesis suggest that workflow disruptions in perioperative material workflows are not merely isolated incidents, but are closely connected to structural conditions in the workflow. In particular, information fragmentation emerged as a recurring explanation for disruption. OR nurses often rely on multiple disconnected information sources when preparing materials for surgery, while experienced staff compensate for this fragmentation through tacit knowledge. This creates a workflow that may function under normal conditions, but becomes vulnerable when information is missing, materials are difficult to locate, or surgeries are rescheduled. The consequence is not only time loss, but also increased cognitive load, and a waste of resources.

Process mapping, visualization, and process mining demonstrated how material-centric workflows can be made more interpretable and presented to different types of stakeholders. The results illustrated the potential of process mining for representing deviations in picking-process sequences, while also showing that high-quality data consisting of timestamps, activity labels, and case identifiers are crucial for meaningful analysis. Digital tools should not only support daily work, but also capture meaningful workflow events. If collected systematically, such high-quality workflow data could be used to define system requirements, visualize workflow behavior, identify recurring disruptions, and support stakeholder-adapted decision support. Furthermore, the thesis shows that different stakeholders require different levels of detail, aggregation, and contextualization.

In conclusion, this thesis provides a framework for understanding and analyzing a perioperative material workflow that is often difficult to observe through existing hospital information systems. While the findings are exploratory and context-specific, the study demonstrates how observational data, when combined with qualitative insight, can reveal workflow disruptions and indicate what future digital systems need to capture. Recommendations for future implementations state that data collection should be a priority when designing digital solutions in the healthcare context, and visualizations must be interpretable and tailored for different stakeholders to provide a foundation for clinically meaningful decision support and reduced cognitive load for healthcare personnel.

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A

Appendix 1

Table A.1: Steps to designing and conducting semi-structured interviews.

Step	Task
1	Determining the purpose and scope of the study
2	Identifying participants
3	Considering ethical issues
4	Planning logistical aspects
5	Developing the interview guide
6	Establishing trust and rapport
7	Conducting the interview
8	Memoing and reflection
9	Analyzing the data
10	Demonstrating the trustworthiness of the research
11	Presenting findings in a paper or report

B

Appendix 2

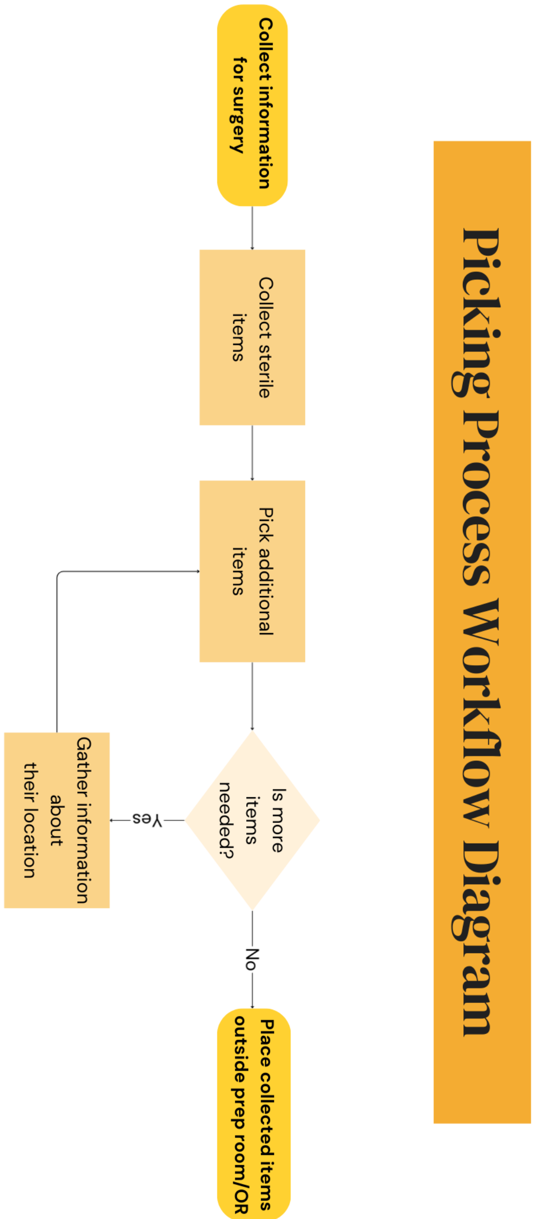

Figure B.1: A process map of the picking process workflow, enlarged for Appendix

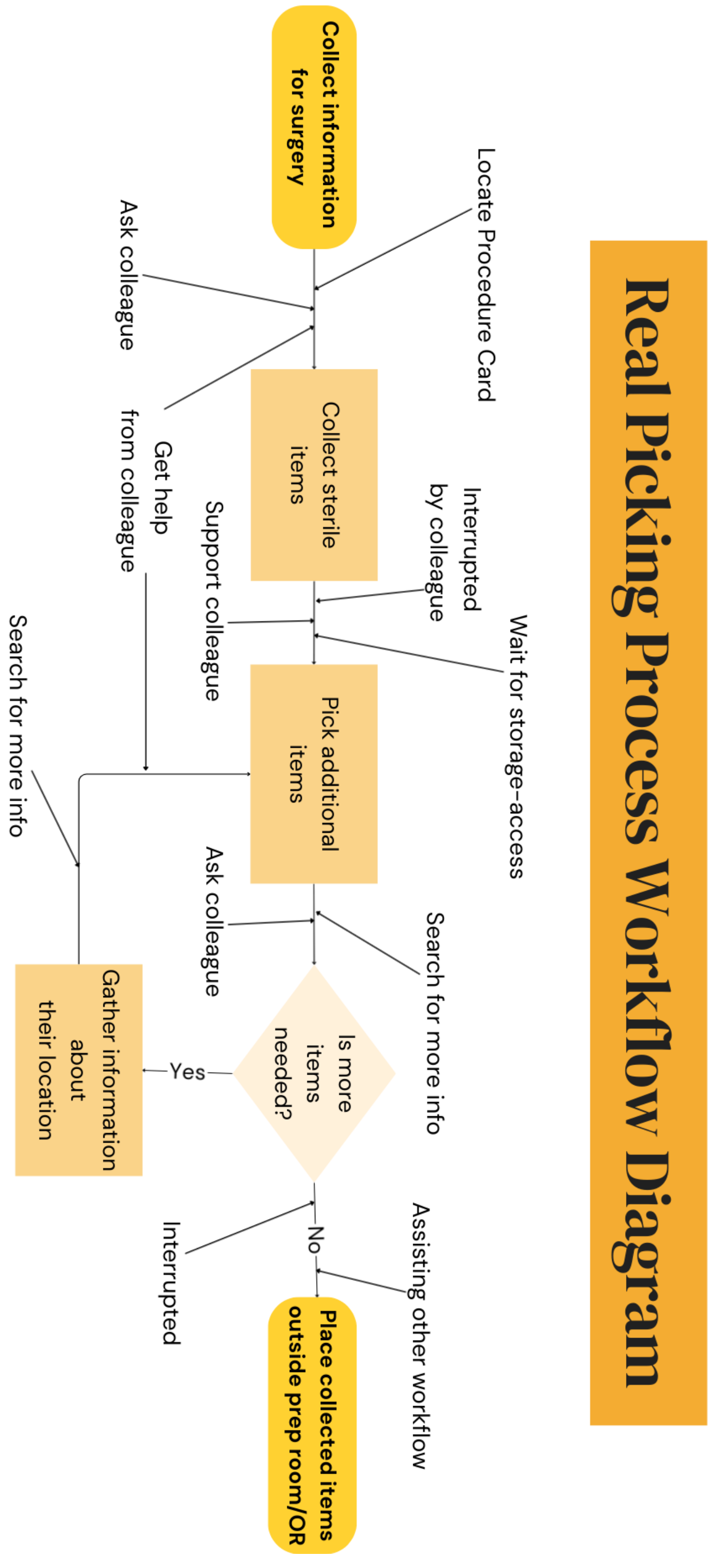

Figure B.2: A process map depicting the reality of the picking process workflow, enlarged for Appendix

C

Appendix 3

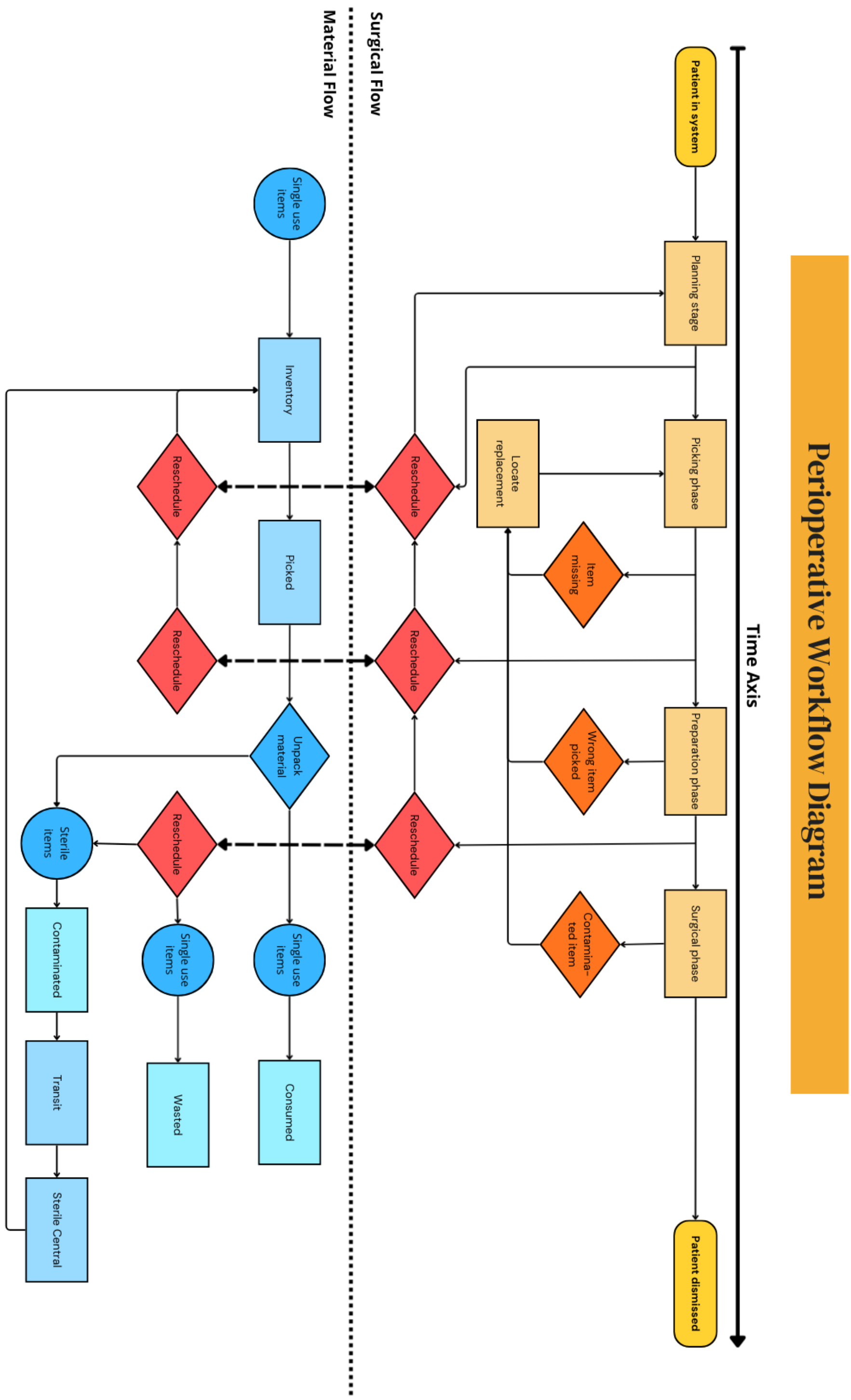

Figure C.1: A process map of the perioperative workflow, as a combination of the surgical and material workflow, enlarged for Appendix

D
Appendix 4

Table D.1: Appendix overview (Part 1): The complete dataset from the shadowing study, with the imputed data

TIMESTAMP	SID	ID	SUR	FIRSTS	OR	SURTYPE	SPICK	EXP	COMPLEX	NRINTER	TOTINTER	TOTINFO	TOTTRANS	TOTWAIT
2024-10-03 08:49:00	2243	101	203	0	2	1	2024-10-03 08:49:00	1	5	0	0	27	25	6
2024-10-01 07:08:00	1111	101	201	1	6	0	2024-10-01 07:08:00	1	3	2	2	11	2	4
2024-10-05 07:25:00	1241	108	203	1	6	0	2024-10-05 07:25:00	4	2	3	20	9	2	3
2024-10-01 11:37:00	2333	107	205	0	3	1	2024-10-01 11:37:00	4	2	1	5	1	4	1
2024-10-01 11:19:00	2221	107	204	0	2	1	2024-10-01 11:19:00	4	2	1	5	1	4	1
2024-10-03 08:50:00	1181	104	201	0	6	0	2024-10-03 08:50:00	3	3	1	2	6	1	5
2024-10-04 08:25:00	1321	102	202	0	5	1	2024-10-04 08:25:00	2	3	1	2	2	1	2
2024-10-03 10:27:00	1242	109	203	0	4	0	2024-10-03 10:27:00	5	2	2	2	7	3	0
2024-10-05 07:25:00	1571	106	201	1	5	0	2024-10-05 07:25:00	4	3	1	2	6	1	3
2024-10-01 08:16:00	1222	101	202	0	7	0	2024-10-01 08:16:00	1	3	0	0	9	1	3
2024-10-04 09:02:00	1166	105	201	0	4	0	2024-10-04 09:02:00	3	3	1	2	6	2	3
2024-10-01 07:58:00	1337	103	204	0	5	0	2024-10-01 07:58:00	2	4	0	0	10	1	0
2024-10-05 08:35:00	2243	111	204	0	3	1	2024-10-05 08:35:00	5	2	1	1	5	2	1
2024-10-01 07:32:00	1221	101	202	1	1	0	2024-10-01 07:32:00	1	2	2	2	5	1	2
2024-10-04 08:49:00	2243	105	204	0	2	1	2024-10-04 08:49:00	3	2	1	2	1	2	1
2024-10-05 10:26:00	1221	110	202	0	7	0	2024-10-05 10:26:00	5	2	1	2	1	1	1
2024-10-03 07:34:00	2333	102	204	0	3	1	2024-10-03 07:34:00	2	4	0	0	0	6	4
2024-10-03 08:31:00	1451	102	205	0	1	0	2024-10-03 08:31:00	2	2	0	0	1	2	1
2024-10-03 09:16:00	1221	104	202	0	5	0	2024-10-03 09:16:00	3	2	2	3	1	1	1
2024-10-04 08:50:00	1221	102	205	0	7	0	2024-10-04 08:50:00	2	3	1	2	3	1	1
2024-10-04 08:41:00	1335	102	203	0	6	0	2024-10-04 08:41:00	2	2	2	2	2	3	0
2024-10-03 07:27:00	2243	103	203	1	4	1	2024-10-03 07:27:00	2	3	1	1	0	5	0
2024-10-05 08:52:00	1221	106	202	0	2	0	2024-10-05 08:52:00	4	2	2	3	2	1	0
2024-10-03 08:44:00	1454	104	205	0	7	0	2024-10-03 08:44:00	3	2	0	0	2	1	1

Table D.2: Appendix overview (Part 2): The complete dataset from the shadowing study, with the imputed data

TIMESTAMP	SID	PICKG	PICKI	PICKD	PICKO	EPICK	TPICK	SPREP	EPREP	TPREP	SSURG	ESURG	TSURG
2024-10-03 08:49:00	2243	18	17	5	0	2024-10-03 10:05:00	76	2024-10-03 10:09:00	2024-10-03 10:43:00	34	2024-10-03 10:52:00	2024-10-03 13:06:00	134
2024-10-01 07:08:00	1111	5	14	0	0	2024-10-01 08:08:00	60	2024-10-01 08:11:00	2024-10-01 08:37:00	26	2024-10-01 08:44:00	2024-10-01 10:04:00	80
2024-10-05 07:25:00	1241	4	5	6	0	2024-10-05 08:03:00	38	2024-10-05 08:06:00	2024-10-05 08:34:00	28	2024-10-05 08:40:00	2024-10-05 10:50:00	130
2024-10-01 11:37:00	2333	10	9	1	0	2024-10-01 11:56:00	19	2024-10-01 11:58:00	2024-10-01 12:19:00	21	2024-10-01 12:25:00	2024-10-01 13:00:00	35
2024-10-01 11:19:00	2221	8	9	2	0	2024-10-01 11:37:00	18	2024-10-01 11:39:00	2024-10-01 12:05:00	26	2024-10-01 12:11:00	2024-10-01 13:46:00	95
2024-10-03 08:50:00	1181	3	10	2	0	2024-10-03 09:06:00	16	2024-10-03 09:11:00	2024-10-03 09:39:00	28	2024-10-03 09:49:00	2024-10-03 11:48:00	119
2024-10-04 08:25:00	1321	6	9	2	0	2024-10-04 08:40:00	15	2024-10-04 08:43:00	2024-10-04 09:11:00	28	2024-10-04 09:17:00	2024-10-04 11:02:00	105
2024-10-03 10:27:00	1242	4	11	0	0	2024-10-03 10:42:00	15	2024-10-03 10:45:00	2024-10-03 11:05:00	20	2024-10-03 11:11:00	2024-10-03 11:52:00	41
2024-10-05 07:25:00	1571	4	12	3	0	2024-10-05 07:39:00	14	2024-10-05 07:41:00	2024-10-05 08:07:00	26	2024-10-05 08:13:00	2024-10-05 09:56:00	103
2024-10-01 08:16:00	1222	2	4	1	0	2024-10-01 08:30:00	14	2024-10-01 08:34:00	2024-10-01 08:59:00	25	2024-10-01 09:07:00	2024-10-01 10:34:00	87
2024-10-04 09:02:00	1166	3	13	1	0	2024-10-04 09:16:00	14	2024-10-04 09:20:00	2024-10-04 09:44:00	24	2024-10-04 09:52:00	2024-10-04 11:16:00	84
2024-10-01 07:58:00	1337	2	7	1	3	2024-10-01 08:12:00	14	2024-10-01 08:16:00	2024-10-01 08:38:00	22	2024-10-01 08:47:00	2024-10-01 09:39:00	52
2024-10-05 08:35:00	2243	8	6	0	0	2024-10-05 08:48:00	13	2024-10-05 08:52:00	2024-10-05 09:14:00	22	2024-10-05 09:22:00	2024-10-05 10:20:00	58
2024-10-01 07:32:00	1221	3	5	1	0	2024-10-01 07:44:00	12	2024-10-01 07:49:00	2024-10-01 08:17:00	28	2024-10-01 08:27:00	2024-10-01 10:23:00	116
2024-10-04 08:49:00	2243	9	6	0	0	2024-10-04 09:00:00	11	2024-10-04 09:03:00	2024-10-04 09:25:00	22	2024-10-04 09:32:00	2024-10-04 10:15:00	43
2024-10-05 10:26:00	1221	3	5	0	0	2024-10-05 10:37:00	11	2024-10-05 10:40:00	2024-10-05 11:01:00	21	2024-10-05 11:07:00	2024-10-05 12:11:00	64
2024-10-03 07:34:00	2333	0	0	3	0	2024-10-03 07:45:00	11	2024-10-03 07:50:00	2024-10-03 08:11:00	21	2024-10-03 08:20:00	2024-10-03 09:09:00	49
2024-10-03 08:31:00	1451	2	5	0	0	2024-10-03 08:40:00	9	2024-10-03 08:44:00	2024-10-03 09:05:00	21	2024-10-03 09:13:00	2024-10-03 09:50:00	37
2024-10-03 09:16:00	1221	3	5	0	0	2024-10-03 09:25:00	9	2024-10-03 09:29:00	2024-10-03 09:52:00	23	2024-10-03 10:01:00	2024-10-03 11:05:00	64
2024-10-04 08:50:00	1221	5	7	1	0	2024-10-04 08:58:00	8	2024-10-04 09:01:00	2024-10-04 09:22:00	21	2024-10-04 09:29:00	2024-10-04 10:03:00	34
2024-10-04 08:41:00	1335	2	9	0	0	2024-10-04 08:49:00	8	2024-10-04 08:52:00	2024-10-04 09:16:00	24	2024-10-04 09:22:00	2024-10-04 10:40:00	78
2024-10-03 07:27:00	2243	0	0	3	0	2024-10-03 07:34:00	7	2024-10-03 07:36:00	2024-10-03 08:01:00	25	2024-10-03 08:06:00	2024-10-03 09:43:00	97
2024-10-05 08:52:00	1221	4	7	0	0	2024-10-05 08:59:00	7	2024-10-05 09:02:00	2024-10-05 09:27:00	25	2024-10-05 09:34:00	2024-10-05 11:01:00	87
2024-10-03 08:44:00	1454	1	7	2	0	2024-10-03 08:49:00	5	2024-10-03 08:51:00	2024-10-03 09:20:00	29	2024-10-03 09:25:00	2024-10-03 11:41:00	136

E

Appendix 5

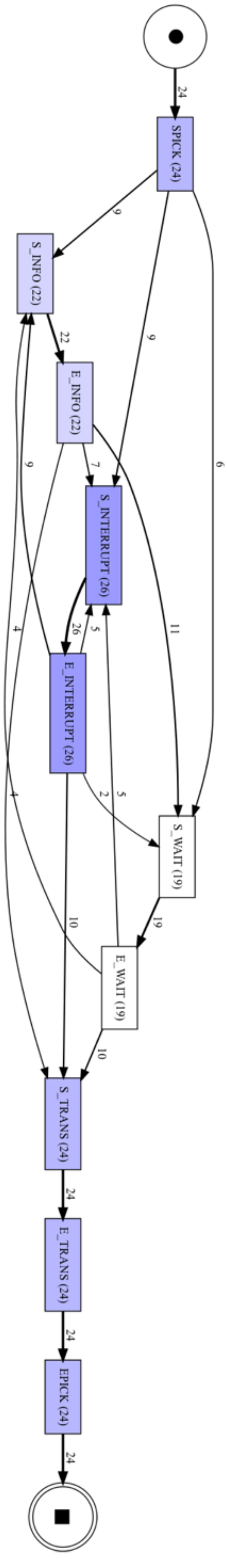

Figure E.1: Showcasing the "Happy path" and deviating paths in the picking workflow, enlarged for Appendix

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